

Hybrid Machine Learning Models for Predicting Energy Consumption in Residential Building Types Using Architectural Features

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Energy management in residential buildings has become an important issue in today's time, as it accounts for a huge amount of energy consumption globally. In residential buildings, an appropriate prediction of energy use helps in promoting energy conservation and aids informed decision-making on issues that can help reduce consumption. Architectural design and building form are very relevant to the growth of energy consumption, mostly in residential areas. The present work is going to develop a model for predicting energy consumption for different types of residential buildings with the help of machine learning methods. In this paper, the SVR and CatBoost algorithms are combined with the HGS method for tuning and optimizing their hyperparameters to improve the accuracy of the predictions. The dataset used in this study comprises over a million records of Irish residential buildings, including terraced houses (type 1), detached houses (type 2), bungalows (type 3), and semi-detached houses (type 4), with 18 input features and two output variables: "Interior Lighting Energy" and "Total Heating Energy." The performance of both models is evaluated using numerical metrics, including MAE and MAPE for each energy variable. It provides insight that the SVR-HGS hybrid model was best at forecasting interior lighting energy with an MAE of 1.6761 and MAPE of 0.0029, and the CatBoost-HGS hybrid model gave the most accurate forecast of total heating energy with an MAE of 1817.8 and MAPE of 0.3587 in the buildings under examination.

Povzetek: Študija obravnava napovedovanje porabe energije v stanovanjskih stavbah z uporabo optimiziranih metod strojnega učenja za izboljšanje natančnosti napovedi.

1 Introduction

The high ratio of energy consumed in buildings has caused many environmental problems. Building energy consumption forecasting is essentially promoted as a way to save energy and enhance decision-making to lower energy usage. Building efficient buildings helps to reduce the total energy consumption in new buildings [1]. Saving and optimizing energy consumption, which is mostly related to non-renewable energies, is important on the one hand due to the limited sources of such energy, and on the other hand, it reduces environmental pollution. The topic of energy management of buildings is very important nowadays because of the building sector's large percentage of energy consumption and the significance of supplying energy and comfort for occupants. Also, building energy management plays an essential role in urban sustainability [2,3]. Observance of the smallest details can have a great effect on reducing consumption in the building. For example, the orientation of the building, the placement of the side spaces, and the improvement of the insulation methods with the lowest cost can improve the efficiency of the settlements. Therefore, by correcting

the construction and design methods of the building, an ideal design can be achieved [4]. Regardless of the different parts of the building, factors such as the way the building is placed and the form of the building also play an effective role in the amount of energy loss. The way of establishment and the form of the building can reduce energy loss in two ways. One is the direction of the sun, and the other is the direction of the wind. The orientation of the building to sunlight and wind depends on the type of climate, and the form of the building can be designed in such a way that it has the necessary coordination with sunlight and wind. The existence of green spaces and trees in the open space can act as a deterrent to heat and cold [5,6]. Advances and setbacks in the building form cause heat loss. Compact plants have less heat loss. About the form of the building, the most important factor is the size of the building. Medium-sized buildings and complexes of office buildings or residential apartments have less heat loss [7].

The architectural design of the building should be done in such a way that it has the least heat exchange, and then, to create a better situation, passive design considerations should be taken into consideration. As the

compact plan reduces the amount of heat loss, the non-compact plan makes it possible to absorb more solar radiation. In hot areas, compressed plans are preferable, and in cold areas, non-compressed plans are preferred, provided that thermal insulation is used. To prevent heat loss, thermal insulations must be designed in such a way that they can also absorb the heat of the sun [8,9]. The walls, floor, roof, and windows are among the parts that are more important than other members of the building. The design of the construction of these parts should be done in such a way that, while being simple in implementation, it does not include a significant increase in cost [10]. Energy consumption in the building sector, especially in residential buildings, due to social development and urbanization, has the largest share among all consumption sectors. Among the factors that determine the amount of energy consumption in the building, we can mention the weather and climatic conditions of the building construction site, the materials and materials used in the outer shell and walls of the building, the type of architecture and structure of the building, and the central facilities of the building (heating and cooling system) [10]. Therefore, it is essential to optimally prevent the wastage of facilities and take steps to save and increase the efficiency of the building. Big data, powerful and affordable computing resources, and advanced machine learning (ML) algorithms have been researched in the building sector in the past decades and have shown their potential to increase building efficiency [11,12]. Recently, artificial intelligence (AI) and ML techniques, in general, have played an effective role in the prediction and performance of building energy, and in the same way, they can play a significant role in the discussion of energy consumption, management, more economical consumption, and finally creating comfort and convenience [13]. AI, as one of the advanced technologies, is used in many fields. One of these fields is saving energy and reducing energy loss. Considering that energy is one of the most important things used in most industries, using AI to predict and reduce energy loss can be very important [14,15]. Therefore, in this study, an attempt was made to provide a hybrid model for predicting energy consumption in residential buildings by focusing on the architecture of buildings, using AI capabilities, and using algorithms based on ML.

Several studies about the research subject are listed below. In a review of research, Fathi et al. (2020) looked into the use of ML to forecast the energy efficiency of urban structures. The results showed that there is no precise criterion for prediction [16]. Walker et al. (2020) researched the accuracy of seven ML-based algorithms for energy prediction in commercial buildings. The case study findings showed that regression tree-based and ANN models are more accurate compared with other models [17]. The model suggested by Seyedzadeh et al. in 2020, aimed at the prediction of energy consumption in non-domestic buildings, in presenting an ML model whose meta-parameters were optimized using an evolutionary algorithm. Its accuracy has been proved while checking statistical indicators [18]. Along similar lines, Pham et al. (2020) identified building energy consumption prediction

in short-term intervals by presenting a model driven through random forests. The results obtained from this article proved the RF model outperforms the M5P and Random Tree models [19]. Additionally, increasing complexity of predicting energy consumption, has been a focus of many recent studies. Machine learning techniques, particularly hybrid models, have been explored for their potential to improve prediction accuracy. For example, recent works, such as those by Rawat et al. (2024) and Adeniji et al. (2022), have demonstrated the effectiveness of combining multiple machine learning methods to achieve improved results in diverse fields, ranging from mental health prediction to cybercrime detection. These studies highlight the importance of integrating advanced algorithms, such as Random Forest and Neural Networks, with optimization techniques to enhance model performance [20–22]. In the paper published by Liu et al., energy consumption was forecasted in public buildings by introducing a model using the support vector machine method. This suggested approach is quite accurate, according to findings of a case study in China [23]. Khan and Byun 2020 proposed a hybrid model developed based on the algorithms of XGBoost, SVR, and KNN optimized by GA as another estimator of energy use. The results of the case study showed that the proposed model outperforms the single machine learning model in terms of accuracy [24]. In this regard, Syed et al. have proposed a new approach to predicting energy consumption in smart buildings using a hybrid deep learning model that includes fully connected layers and LSTM. The investigation of evaluation metrics proved the accuracy of the proposed approach [25]. Ardabili et al. have explored the accuracy of ML and DL-based algorithms in building energy prediction. Results have shown that the hybrid model based on DL, and based on SVM was more accurate [26]. Olu-Ajayi et al. (2022) presented a model for the prediction of energy consumption at the building design stage through the assessment of different ML and DL algorithms. It can be viewed that different algorithms provide the best results when using DNN among other evaluated algorithms [11]. Olu-Ajayi et al. (2022) investigated the application of ML in predicting building energy consumption in the design phase. In this study, while investigating the effect of feature selection on the accuracy of predictions, it was shown that the Gradient Boosting (GB) algorithm is the most accurate among ML methods [27]. The literature study revealed that a range of models and techniques have been proposed thus far to forecast building energy consumption; each has unique benefits and features and has been applied to the circumstances of the issue. Table 1 summarizes the performance and methodologies of various studies on energy prediction in buildings, focusing on machine learning algorithms. It highlights the types of datasets used, the accuracy metrics obtained, and the gaps identified in each study. The comparison reveals the areas where these studies are limited, such as the focus on commercial or non-domestic buildings, lack of architectural feature integration, and the absence of hyperparameter tuning, which are addressed in our proposed approach. However, in all studies, the efficiency

and application of ML-based methods in predicting energy consumption have been emphasized. On the other hand, architecture and building form play a fundamental role in energy consumption in buildings, especially residential buildings.

Table 1: A summary of the findings and research gaps in recent related studies.

Study/Reference	Algorithms/Methods Used	Datasets Utilized	Results (Accuracy Metrics)	Gaps Identified
S. Walker et al. (2020) [17]	Various ML algorithms	Commercial building data	R2: 0.85	Focused on aggregated energy performance, not residential buildings.
S. Seyedzadeh et al. (2020) [18]	Machine Learning	Non-domestic building data	Accuracy: 90%	Limited to non-domestic buildings, no detailed architectural integration.
S. K. Baduge et al. (2022) [19]	AI, Deep Learning	Construction building data	Accuracy: 93%	Primarily focused on construction 4.0, lacks detailed energy consumption prediction.
P. W. Khan & Y.-C. Byun (2020) [24]	Genetic Algorithm, Hybrid ML	Not specified	MAE: 2.5	No comparison with other state-of-the-art methods, lacks integration with architectural factors.
D. Syed et al. (2021) [25]	Hybrid Deep Learning	Smart building data	MAPE: 5%	Does not incorporate architectural or building form features.
S. Ardabili et al. (2022) [26]	Deep Learning, ML	Various building energy data	Accuracy: 95%	Lacks feature optimization and hyperparameter tuning.

The state-of-the-art (SOTA) methods reviewed above primarily focus on generalized energy prediction without accounting for architectural features and specific residential building types. This study improves upon these methods by incorporating architectural design, building forms, and advanced hyperparameter tuning using SVR-HGS and CatBoost-HGS models. This approach provides higher accuracy for both lighting and heating energy predictions and addresses the limitations of previous methods regarding feature integration and optimization. The contribution of this study lies in its integration of three key advancements that address limitations observed in prior works. First, unlike many previous studies that relied on either general energy datasets or abstracted variables, this work leverages a highly detailed and diverse dataset generated through parametric simulation, incorporating architectural, thermal, and operational features of residential buildings. Second, it introduces a hybrid modeling framework that couples well-established learners—SVR and CatBoost—with the Hunger Games Search algorithm for advanced hyperparameter optimization. While similar algorithms have been individually explored in the literature, their hybridization within the context of detailed residential energy modeling remains underrepresented. Third, the study offers a comprehensive evaluation across four residential building types, emphasizing not only accuracy but also practical deployment aspects such as runtime and generalizability. This holistic design bridges the gap between model precision and real-world applicability, making the contribution both technically novel and practically significant. In this study, an attempt was made to provide

a model for predicting energy consumption in different types of residential buildings by using the capabilities of ML-based methods. The rest of the paper is mentioned as follows: In Section 2, the research methodology, including the introduction of algorithms and hybrid models, was presented. Section 3 introduced the research dataset and studied the effect of different variables with respect to energy consumption. Section 4 discussed the findings of the research in terms of output variables. Finally, Section 5 represents the conclusions.

2 Methodology

This research proposes a hybrid machine learning model to forecast energy consumption for various house building types. The research discussion includes four building styles: bungalows, semi-detached buildings, terraced buildings, and detached buildings. There are 18 input features and two output variables, which are "interior lighting energy" and "total heating energy." Two machine learning algorithms, namely CatBoost and Support Vector Regression (SVR), have been used to develop models with substantial predictability. CatBoost is a gradient-boosting algorithm for decision trees that efficiently handles categorical and ordinal features. Support Vector Regression, also called the extension of SVM for the regression task, is another algorithm that has been used in this research. In order to improve their prediction accuracy, both algorithms are hybridized with a meta-heuristic optimization technique known as Hunger Games Search or, in short, HGS—hence, the two hybrid models: CatBoost-HGS and SVR-HGS. These hybrid models can bring out the best in these primary algorithms by

optimizing and fine-tuning their hyperparameters. The K-fold cross-validation approach, where k=5, will be used to evaluate their performances. Cross-validation involves the division of the dataset into K equal-volume segments. It uses K-1 folds as training data and the remaining fold as test data in each iteration. The training data is used to train the model, and the test data is used for validation. Steps one and two are repeated K times, each time using a different fold as the test data. Lastly, the results of all K iterations are averaged. The choice of k=5 was made as a balance between computational efficiency and the reliability of performance estimation. Smaller values of k (e.g., 2–4) may lead to high variance in evaluation due to fewer training samples per fold, while larger values (e.g.,

k=10) increase the computational cost significantly, particularly when combined with hyperparameter tuning. Based on prior literature and standard practices in regression tasks, 5-fold cross-validation offers a practical compromise with low bias and acceptable variance. The accuracy of the proposed models is assessed through various evaluation indices, including MAE (Mean Absolute Error), MAPE (Mean Absolute Percentage Error), NRMSE (Normalized Root Mean Squared Error), and RAE (Relative Absolute Error), as detailed in Table 2. This evaluation is performed across different types of residential buildings using a case study to determine the effectiveness of the models [28–31].

Table 2: Statistical evaluation indices

Index	Name	Equation
NRMSE	Normalized Root Mean Square Error	$NRMSE = \frac{\sum_{i=1}^{num} (\Delta_1)^2}{\sum_{i=1}^{num} y_i^2}$
MAPE	Mean Absolute Percentage Error	$MAPE = \frac{1}{num} \sum_{i=1}^{num} \left \frac{\Delta_1}{y_i} \right $
MAE	Mean Absolute Error	$MAE = \frac{\sum_{i=1}^{num} \Delta_1 }{num}$
RAE	Relative Absolute Error	$RAE = \frac{\sum_{i=1}^{num} \Delta_1 }{\sum_{i=1}^{num} \Delta_2 }$

The values in this table are as follows: y_i is the i th observed value, \hat{y}_i is the i th estimated value, and \bar{y} is the mean of observations, no is number of observations, $\Delta_1 = y_i - \hat{y}_i$, $\Delta_2 = y_i - \bar{y}$.

2.1 The CatBoost-HGS Hybrid Model

In this section, more details of the Catboost-HGS hybrid model are discussed, which is a Catboost method optimized by the HGS algorithm. The HGS algorithm attempts to minimize the cross-validation loss (error) by optimizing the hyper-parameter values. The main algorithm for predicting output variables is the Catboost algorithm. Engineers and researchers at Yandex created the gradient-boosting algorithm CatBoost in 2017. It is based on decision trees. Because the CatBoost technique uses symmetric trees, it is incredibly fast in the prediction domain [32]. One factor that makes CatBoost so powerful

is its low latency (coverage) requirements, which means it's about eight times faster than XGBoost. The key characteristic of CatBoost is its great stability, demonstrated by the fact that, unlike other ML models, it does not require a large amount of training data and can operate on a wide range of data types [33]. CatBoost's library is open source and available for free. We can list self-driving cars, weather forecasting, and other uses for this method [29]. A few of CatBoost's primary benefits are its higher quality when compared to competing GBDT libraries, its exceptional category inference speed, its support for both numerical and categorical characteristics, and the availability of data visualization tools [34]. Among the various hyperparameters of the CatBoost model, the focus was on optimizing two key parameters, as shown in Table 3, using the Hunger Games Search (HGS) algorithm:

Table 3: Hyperparameter tuning results using HGS

Hyperparameter	Search Range	Final Value (Selected by HGS)
Learning-rate	[0.3, 0.01]	0.08
depth	(integers) [10, 4]	8

These two parameters were selected due to their significant influence on the model's learning dynamics and capacity. The HGS algorithm was applied to explore the defined ranges and identify the combination that

minimized the validation loss. The final values identified by the algorithm led to improved model performance and generalization capability. The flowchart of the CatBoost-HGS hybrid model is shown in Fig. 1.

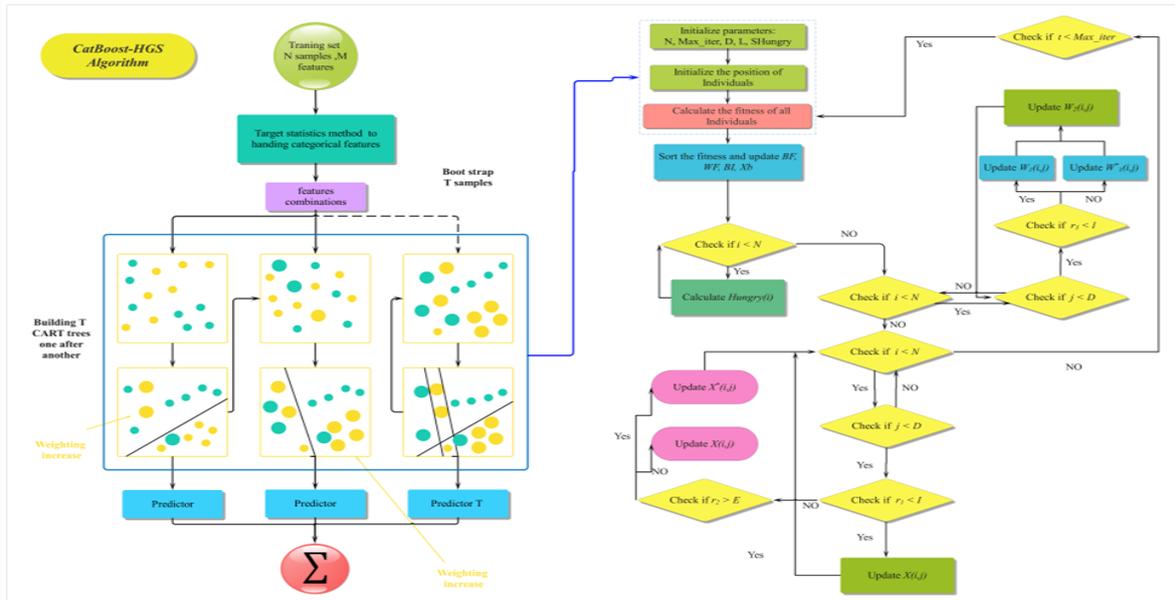


Figure 1: Flowchart of the CatBoost-HGS hybrid model

The training dataset, number of samples (N), and number of features (M) are chosen to initialize the model, as shown in Figure 1. The target statistics (TS) technique is then applied to the categorical features. All of the category qualities were then combined to form new combinations. The next parts will build T regression trees (CART) one by one. In the end, an average of the predictors' values will produce a more accurate model forecast [35]. During network training, the K-Fold cross-validation technique is also used to prevent over-fitting. If the stopping condition allows it, which is frequently the maximum number of iterations, the optimization technique (HGS) is executed each time the loop is restarted.

The initialization of the parameters, the positions of the people, and the fitness values of the individuals are all determined first in the succinct description of the HGS algorithm. Next, the fitness values are sorted to update the parameters. Ultimately, the weight of hungry behavior (W_1 and W_2), as well as the location of each person in the search area, are established by looking at a few conditions and creating random numbers. The method delivers the computed optimal values to the Catboost algorithm and terminates upon the occurrence of the stop condition, which is typically the maximum number of repetitions. Note that a more thorough explanation of the HGS algorithm's governing equations may be found in the next section.

2.2 The SVR-HGS Hybrid Model

In this section, more details of the SVR-HGS hybrid model are discussed, which is a Catboost method optimized by the SVR algorithm. In this model, the main

algorithm is to predict the output variables of SVR. An ML method for regression tasks is called SVR. For regression issues, SVR is an extension of SVM. The objective of SVR is to identify a function that roughly represents the mapping between the continuous output variable and the input variables, or features. The algorithm's goal is to minimize the deviation between the actual and anticipated values while maintaining a certain tolerance margin. Labeled training data with associated continuous goal values and input feature pairs is needed for support vector machines (SVR). To make sure the input characteristics have comparable ranges, it is crucial to scale them. Kernel functions are used to convert the SVR input properties into a higher-dimensional space. Sigmoid, polynomial, linear, and radial basis function (RBF) kernels are commonly used. In the converted feature space, the SVR method locates the ideal hyperplane that minimizes error and maximizes margin. Constrained optimization problems must be solved throughout the training phase. The SVR model may be assessed using appropriate metrics after it has been trained. By converting the input characteristics using the learned mapping and applying the regression function, the trained SVR model may make predictions on fresh, unknown data. For regression tasks, SVR is an effective method, particularly when handling intricate, non-linear connections between features and goals. Predicting continuous values is crucial in several fields, including engineering, economics, and finance, where it is commonly employed [36–38]. Fig. 2 shows the flowchart of the SVR-HGS hybrid model. This flowchart illustrates how the HGS algorithm is combined with the main SVR neural network to optimize the SVR's hyper-parameters (ϵ , γ , and C).

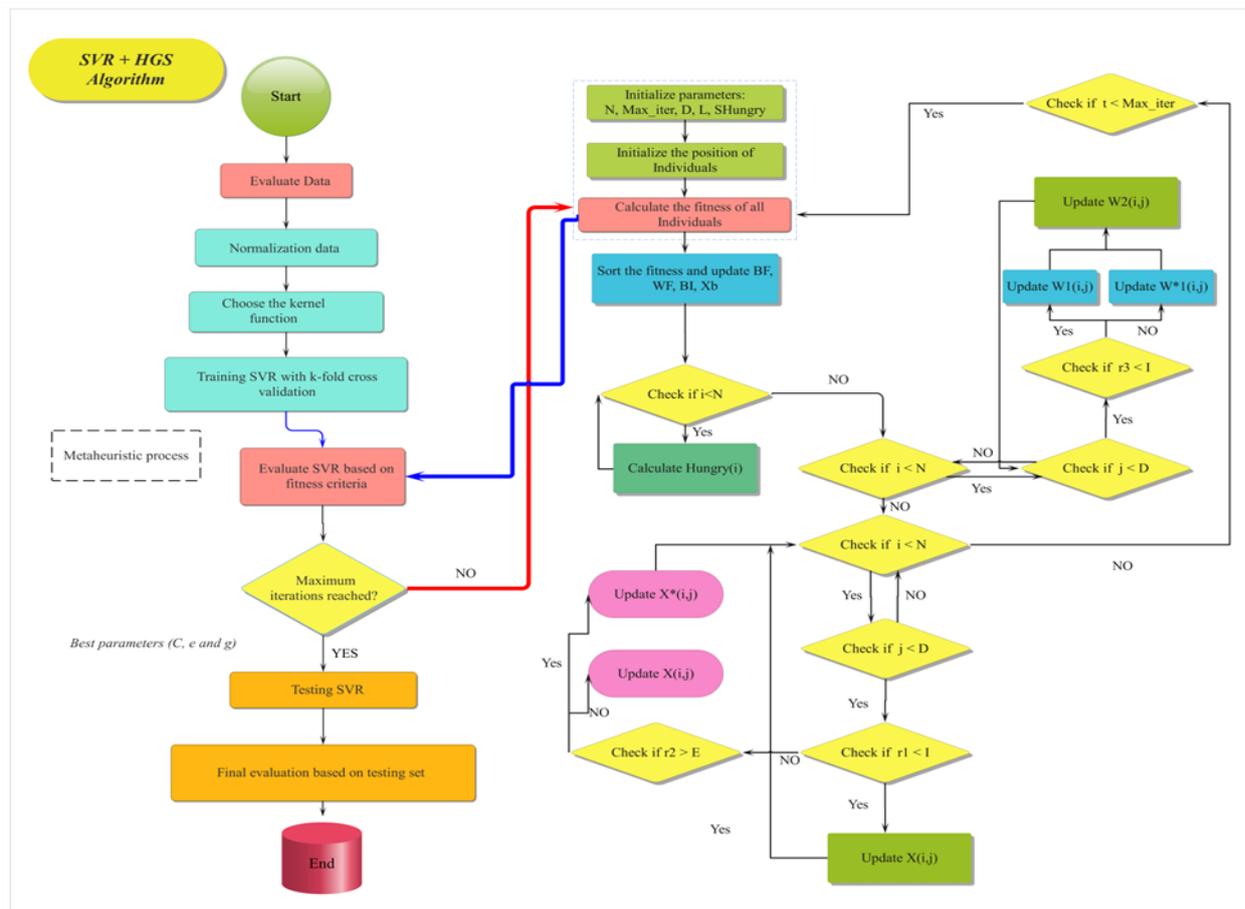


Figure 2: Flowchart of the SVR-HGS hybrid model

The algorithm begins on the left side of the flowchart, corresponding to the SVR algorithm, as shown in Fig. 2. After data normalization, the type of kernel function used will be specified. Several common kernels can be used, including polynomial, linear, and Gaussian kernels, also known as Radial Basis Function (RBF) kernels. For this investigation, the RBF kernel is the default function. The data will then be trained using the K-fold cross-validation process. Next, the HGS algorithm will be used to optimize the hyperparameters of the SVR model, enhancing the training procedure. The role of the HGS algorithm in this context is similar to its role in the CatBoost-HGS hybrid model explained in the previous section. The HGS algorithm will continue to run until the termination condition is met. Once this condition is satisfied, the optimal hyperparameter values will be applied to retrain the SVR model. Finally, statistical indices will be used to calculate the model's fitness quality. This cycle will continue until the specified number of iterations is completed.

In comparison to commonly used metaheuristic algorithms such as Genetic Algorithms (GA) and Particle Swarm Optimization (PSO), the Hunger Games Search (HGS) algorithm provides a more adaptive and diversity-preserving optimization process. HGS utilizes stochastic hunger-based adjustments to guide the population, reducing the risk of premature convergence often encountered in GA or PSO. Additionally, its structured

balance between exploration and exploitation makes it suitable for tuning sensitive models like SVR and CatBoost, where parameter interactions are highly non-linear. These characteristics make HGS particularly effective for achieving global optima in complex learning systems. The hybridization of CatBoost and SVR with Hunger Games Search (HGS) was intended to enhance the hyperparameter tuning process through a more intelligent and adaptive search strategy. Standard techniques such as grid search or random search often suffer from inefficiency or failure to capture complex parameter interactions, particularly in high-dimensional search spaces. By integrating HGS, which uses a dynamic hunger-driven mechanism for population update, the models benefit from better exploration of the search space and convergence towards globally optimal configurations. This combination enables more robust generalization performance, as confirmed by the empirical results.

2.3 Hunger Games Search (HGS) Algorithm

Yang et al. introduced the HGS algorithm in 2021. The main inspiration of this algorithm was the collaborative behavior of animals in nature in order to search for food in times of hunger. When food resources are limited, there will be a logical game between hungry animals to search and find food and win in this situation. The

implementation steps of this algorithm are described as follows [36]:

The first step of this algorithm is to find food. In this step, cooperative communication of animals and food search behavior is expressed using the following equations [39]:

$$\vec{X}(t+1) = \begin{cases} Game_1 = \vec{X}(t) \cdot (1 + randn(1)) & r_1 < l \\ Game_2 = \vec{W}_1 \cdot \vec{X}_b + \vec{W}_2 \cdot \vec{R} \cdot |\vec{X}_b - \vec{X}(t)| & r_1 > l, r_2 > E \\ Game_3 = \vec{W}_1 \cdot \vec{X}_b - \vec{W}_2 \cdot \vec{R} \cdot |\vec{X}_b - \vec{X}(t)| & r_1 > l, r_2 < E \end{cases} \quad (1)$$

In these equations, r_1 and r_2 represent random numbers between of 0 and 1, $randn(1)$ represents random normal distribution, and the value of t represents the current iteration, \vec{W}_1 and \vec{W}_2 express the weight of hunger behavior, parameters \vec{X}_b and $\vec{X}(t)$ indicate the position of the best individual and each individual at iteration t , respectively, \vec{W}_1 and \vec{W}_2 express the weight of

hunger behavior, the l variable is designed to improve the algorithm, and \vec{R} is a variable in the range of a and $-a$, which is defined as the following equation [40]:

$$\vec{R} = 2 \times shrink \times rand - shrink \quad (2)$$

$$shrink = 2 \times \left(1 - \frac{t}{T}\right) \quad (3)$$

T is the maximum number of iterations, while $rand$ stands for random values between 0 and 1. The equation for variable E , a change control in all circumstances, is shown below [41]:

$$S = hyp.func(|fitness_i - fitness_{best}|) \quad (4)$$

Where $hyp.func$ refers to hyperbolic function, $fitness_{best}$ refers to the best fitness value, and $fitness_i$ represents the obtained fitness in the current iteration. The HGS algorithm's search procedure and reasoning during optimization based on Eq. (1) are depicted in Fig. 3.

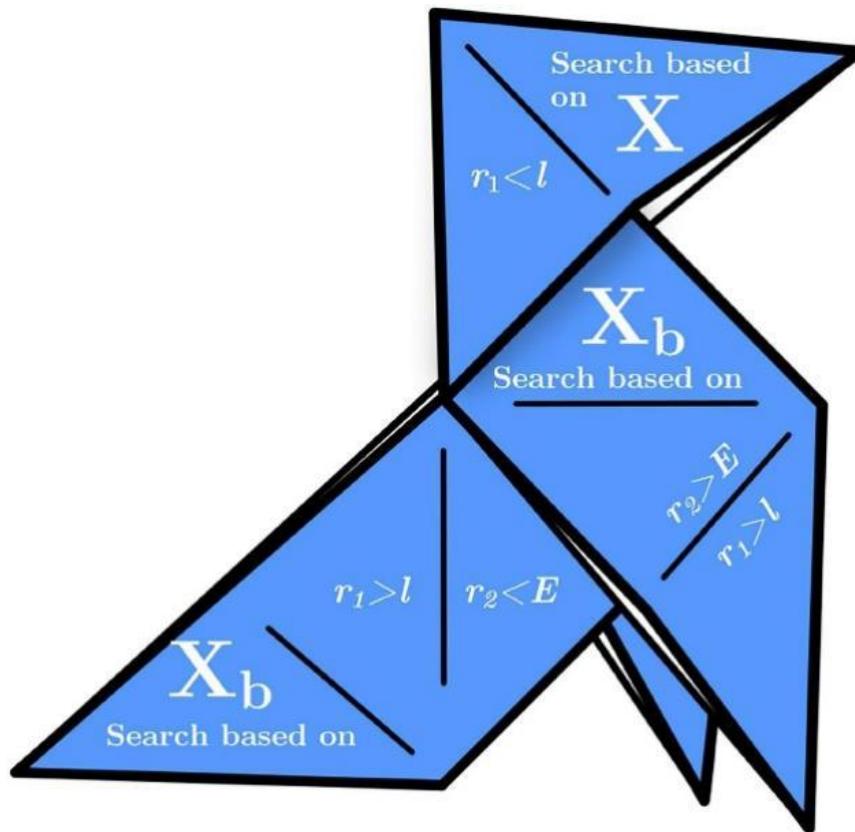


Figure 3: Logic of HGS algorithm during optimization

In the second step of this algorithm, which involves the role of hunger, the characteristics of the members' hunger coefficient in the search are explained by \vec{W}_1 and \vec{W}_2 , whose equations are expressed as follows [36]:

$$\vec{W}_1 = \begin{cases} \delta(i) \cdot \frac{N_{pop}}{\sum \delta} \times r_4 & r_3 < l \\ 1 & r_3 > l \end{cases} \quad (5)$$

$$\vec{W}_2 = (1 - \exp(-|\delta(i) - \sum \delta|)) \times r_5 \times 2 \quad (6)$$

Where the number of individuals is indicated by the parameter N_{pop} , r_3 , r_4 , r_5 , and r_6 are parameters that

create random numbers between 0 and 1. The hunger of every individual is represented by $\delta(i)$, which may be computed using the equation [37]:

$$\delta(i) = \begin{cases} 0 & fitness_i == fitness_{best} \\ \delta(i) + \delta_{new} & fitness_i \neq fitness_{best} \end{cases} \quad (7)$$

Where δ_{new} shows a new hunger, which is defined as the following equation [38]:

$$\delta_{new} = \begin{cases} \delta_{largest} \times (1 + r) & \delta_{temp} < \delta_{largest} \\ \delta_{temp} & \delta_{temp} \geq \delta_{largest} \end{cases} \quad (8)$$

$$\delta_{temp} = \frac{fitness_i - fitness_{best}}{fitness_{worst} - fitness_{best}} \times r_6 \times 2 \times (bound_{upper} - bound_{lower}) \quad (9)$$

Where $fitness_{worst}$ denotes the lowest fitness attained in the current iteration, $bound_{upper}$ and $bound_{lower}$ represent the higher and lower boundaries of the feature space, respectively, r_6 is parameters that create random numbers between 0 and 1, and $\delta_{largest}$ is designed to improve the performance of the algorithm [38].

The integration of Hunger Games Search (HGS) with SVR and CatBoost optimizes hyperparameters by using a population-based search mechanism. HGS adjusts key parameters such as the regularization parameter (C) and epsilon for SVR, and learning rate, number of trees, and depth for CatBoost. The algorithm iteratively refines candidate solutions based on performance, improving both models' accuracy by identifying optimal parameter sets. This method provides a more efficient search process compared to traditional methods like grid or random search.

All initialization settings used in the optimization algorithm including population size, number of iterations, and random seed along with the model configuration parameters, have been clearly specified. These implementation details are presented in Table 4 and further described.

Table 4: Configuration Details of the HGS Algorithm and CatBoost Model

Component	Parameter	Value	Description
HGS Algorithm	Population size	30	Number of individuals in the search population
	Max iterations	100	Total optimization steps
	Random seed	42	Ensures reproducibility of search path
	Initialization range	[0, 1]	Normalized range for initializing solutions
	Objective function	Validation loss	Metric to minimize during tuning
CatBoost Model	Iterations	600	Number of boosting rounds
	Learning rate	0.08	Step size shrinkage
	Depth	8	Maximum tree depth
	Loss function	RMSE	Used for regression task
	Eval metric	RMSE	Used for early stopping and comparison
	Early stopping rounds	50	Stops training if no improvement after 50 rounds
	Random seed	42	Controls randomness in model training

3 Description of dataset

The dataset used in this study comprises over a million records of Irish residential buildings, including terraced houses (type 1), detached houses (type 2), bungalows (type 3), and semi-detached houses (type 4). The four building types selected for this study terraced houses, detached houses, bungalows, and semi-detached houses were chosen based on their representation of common residential structures with varying energy consumption characteristics. These building types are widely observed in global energy studies, as they cover a broad spectrum of architectural designs and thermal dynamics. For example, detached houses are often used in energy consumption studies due to their energy performance variability, while terraced houses are frequently studied in urban settings due to their dense arrangement and shared walls. This diversity allows for a more comprehensive analysis of energy consumption patterns across different residential configurations. Furthermore, the choice of these building types aligns with existing literature, which highlights their significance in residential energy usage across various climates and geographical regions. Figure 4 illustrates the geometric models of these various building types. The dataset includes 18 input features and two output features: "Interior Lighting Energy" and "Total Heating Energy." It integrates EnergyPlus for thermal

simulation with jEPlus, a parametric tool for physics-based simulations, and incorporates DesignBuilder building templates for generation. DesignBuilder was utilized to create baseline architectural models, which were then exported to EnergyPlus-compatible IDF files. These were linked with jEPlus to run batch simulations across varying feature values. Assumptions included the use of standard occupancy schedules and fixed weather files per region, while HVAC templates were selected from pre-validated DesignBuilder libraries. One limitation is that jEPlus assumes linear parameter variation between specified bounds, which may not fully capture nonlinear effects of design changes. Additionally, while DesignBuilder automates geometry export, it may constrain fine-tuning of certain envelope properties. Additionally, the dataset is geographically specific, representing only Irish building types and climate conditions. geographic limitation may introduce biases, as energy consumption behaviors and architectural features can vary significantly across different regions and climates. While the models performed well within the context of Irish buildings, their generalizability to other geographic locations or climates may require further validation with more diverse datasets. The dataset encompasses U-values for walls, roofs, floors, doors, and windows, as well as data on building fabric qualities, HVAC systems, and other components. Additionally, it

includes metrics for hot water energy demand, solar systems, equipment, lighting, and heating.



Figure 4: The geometric model of different residential building types

To investigate the effect of different features on energy consumption across various building types, Figures 5-8 illustrate the correlation between the research variables for each building type separately. In all building types, a positive correlation exists between the insulation values (U-Values) for floors, doors, roofs, windows, and walls and both output variables. This indicates that as the U-values increase, which signifies poorer insulation quality, both "Interior Lighting Energy" and "Total Heating Energy" also rise. Correlation values between HVAC Efficiency and output variables are negative across all building types. This suggests that increasing HVAC efficiency is likely to significantly reduce energy consumption, as effective heating and cooling systems have a major impact on energy use in residential buildings. The positive correlation values found between Domestic

Hot Water Usage, Air Change Rate, and the output variables across all building types indicate that these factors have a notable impact on energy consumption. Additionally, there are positive correlations between Building Orientation, Equipment Density, and Heating Setpoint Temperature, and the output variables, reflecting a direct relationship between these factors and energy consumption. In contrast, the correlation values between the Weather File, Occupancy Level, and Window-to-Wall Ratio with the output variables are close to zero for all building types, suggesting no significant correlation. Furthermore, the correlation values between Lighting Density and Heating Setback Temperature with the output variables are positive in all building types, indicating a direct relationship between these factors and energy consumption.

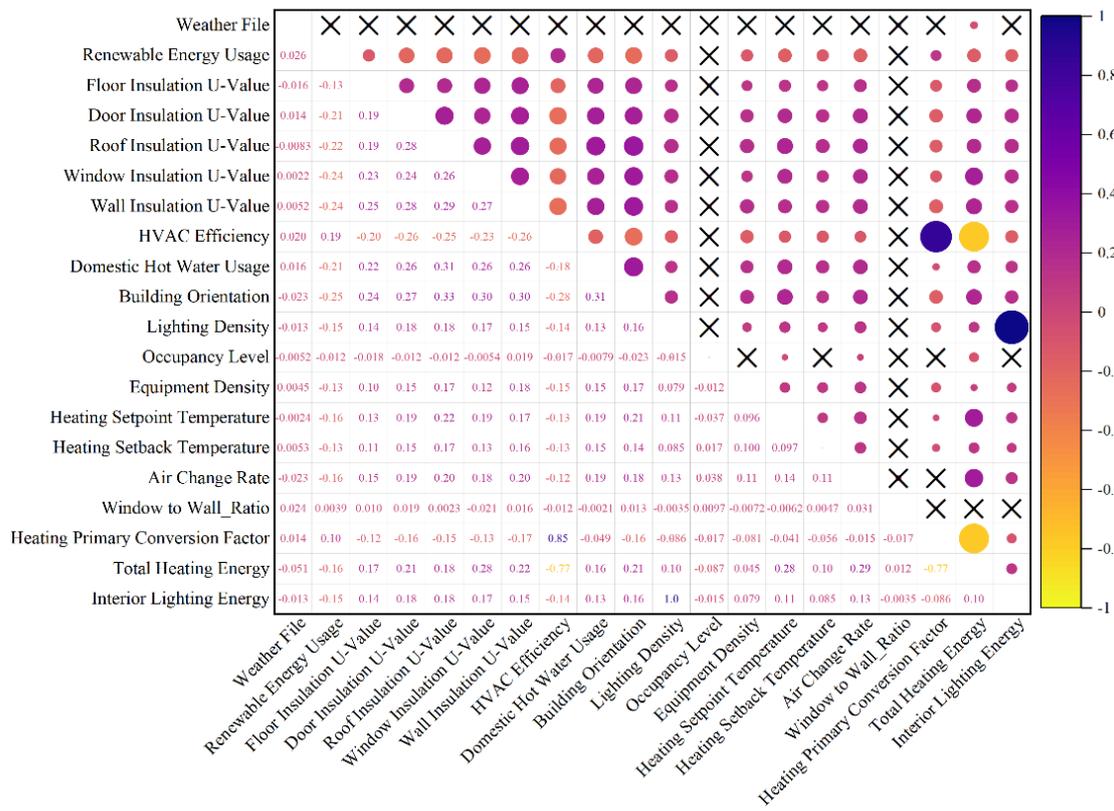


Figure 5: Correlation between research variables in type 1 building

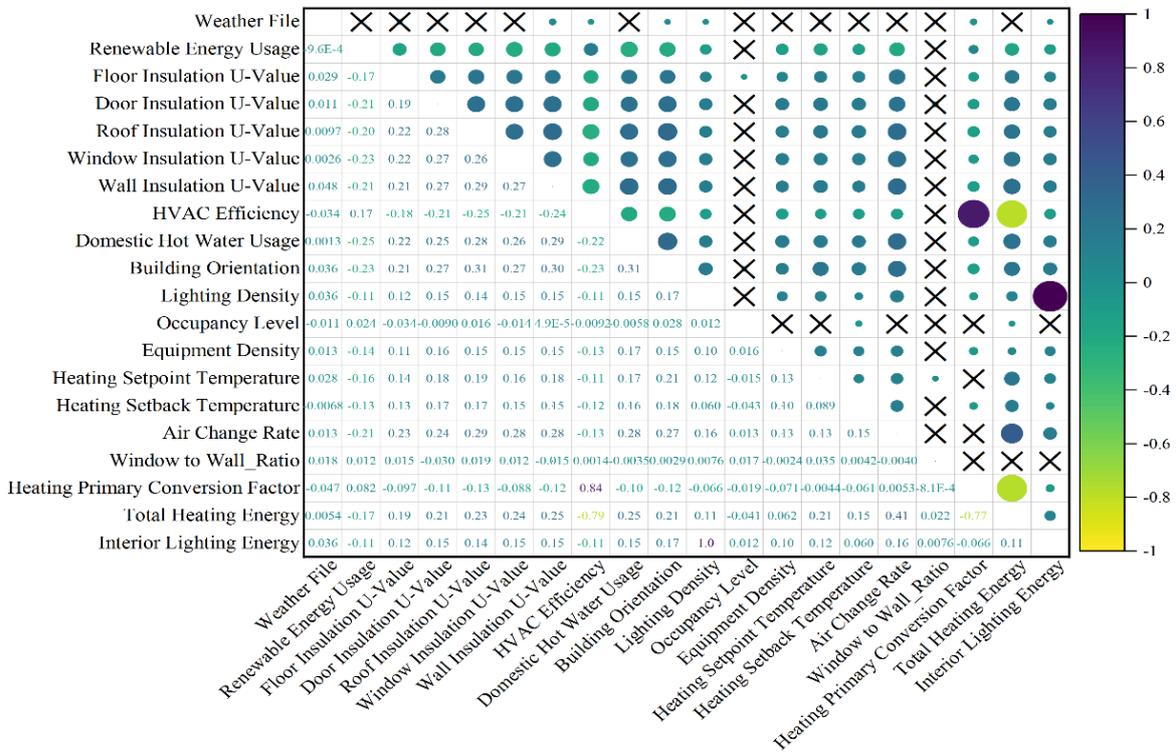


Figure 6: Correlation between research variables in type 2 building

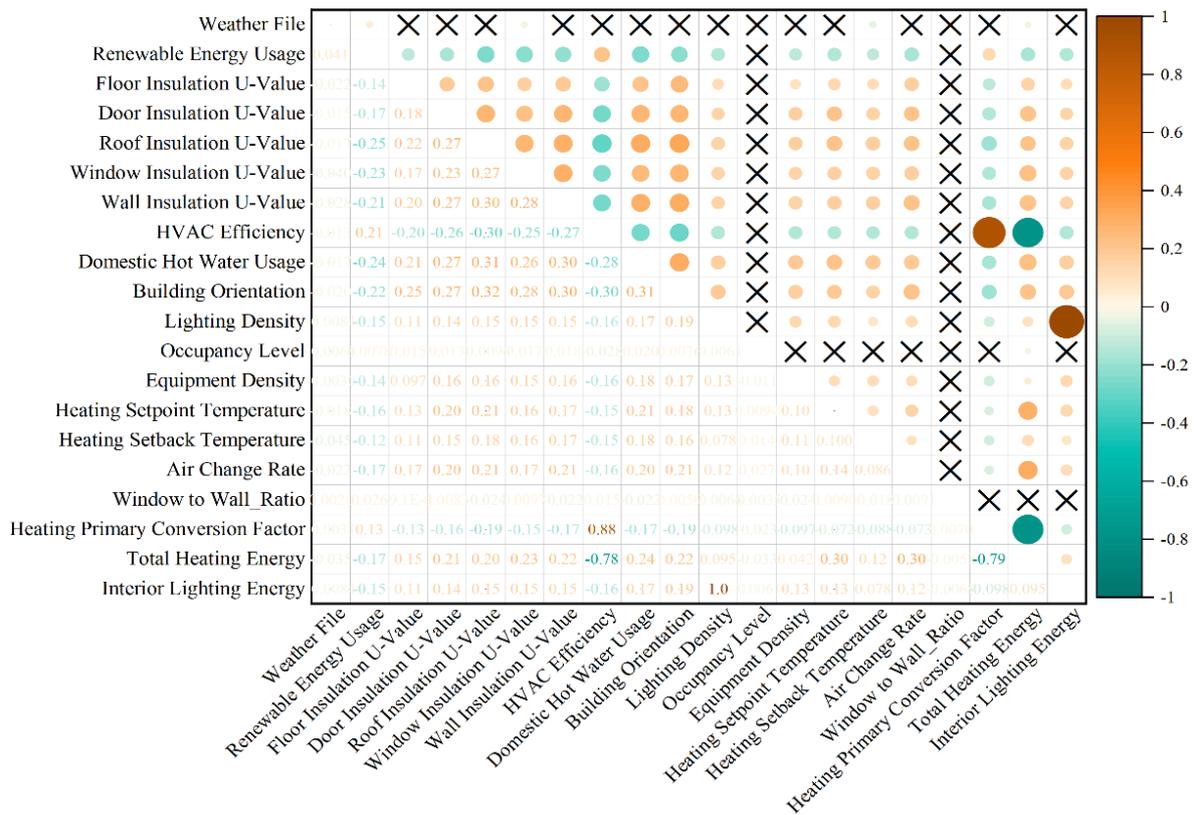


Figure 7: Correlation between research variables in type 3 building

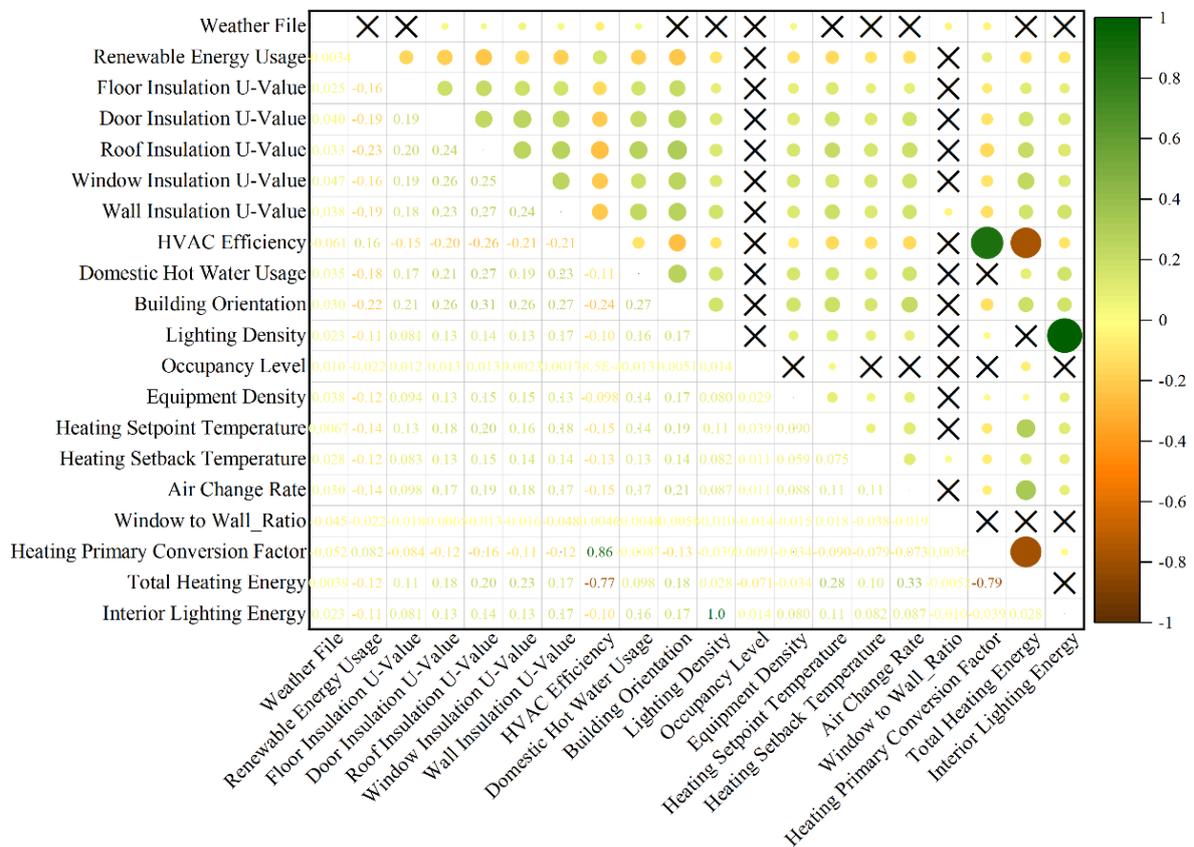


Figure 8: Correlation between research variables in type 4 building

The analysis of the correlation results presented in Figures 5 to 8 reveals that certain variables, such as HVAC efficiency, exhibit a strong correlation with energy consumption, particularly heating energy. This strong correlation is expected, as HVAC systems play a significant role in regulating building temperatures and, therefore, energy consumption. On the other hand, variables like weather file and building orientation show weaker correlations with energy consumption. This can be attributed to the relatively stable nature of these factors over time, particularly in fixed climates or locations, which reduces their impact on energy consumption compared to other dynamic variables, such as heating setpoint temperature or air change rate. These findings underscore the importance of carefully selecting and integrating relevant features for energy consumption prediction. The choice of architectural features, as well as hyperparameter tuning, contributes to the observed differences in model performance. The incorporation of HVAC efficiency and heating-related parameters into our models helps capture the complexities of energy consumption more accurately, as opposed to simpler models that do not account for these factors. Although all 18 input features were initially included in the model, their respective correlations with the target energy variables were further analyzed to assess their actual contribution to prediction performance. As illustrated in Figures 5–8, some features such as Weather File, Occupancy Level, and Window-to-Wall Ratio exhibited low correlation with both interior lighting and heating energy consumption. To evaluate their influence, additional ablation tests were conducted, revealing that the exclusion of these low-correlation variables did not significantly degrade the model's accuracy. However, given their potential contextual importance in specific scenarios and to maintain generalizability across diverse building configurations, these features were retained in the final model. This approach balances model comprehensiveness with complexity, ensuring robustness without overfitting to specific input patterns. These insights highlight the contributions of this study to improving energy consumption predictions by addressing the limitations of current methods in the literature.

3.1 Data preprocessing

In order to prepare the dataset for model training and ensure that it was clean and suitable for the algorithms, several preprocessing steps were applied. These steps

were designed to handle missing values, scale the data, and account for the different characteristics of the variables, ensuring compatibility across models and comparison with baseline methods. Instances with missing target values were removed, and for numerical features with missing values, mean imputation was applied. Categorical features with missing values were treated as a separate category ("Missing") to preserve useful information. Although CatBoost handles categorical variables and does not require explicit normalization of numerical features, Min-Max scaling was applied to numerical inputs to improve the performance of other algorithms used for baseline comparisons. CatBoost also performs internal encoding of categorical features based on target statistics, so manual encoding was not required. Outliers were detected and removed based on domain knowledge, with values exceeding the 99th percentile in selected features being capped. These preprocessing steps ensured the dataset was clean, consistent, and ready for training, while maintaining comparability across algorithms. All preprocessing and modeling tasks were implemented in Python 3.9.13. The experiments were conducted on a system equipped with an Intel Core i7-11700K CPU, 32 GB of RAM, and an NVIDIA RTX 3080 GPU. The following libraries were used: CatBoost 1.2.2, Scikit-learn 1.1.3, and NumPy 1.23.5.

4 Results

In this section, the accuracy of various models is evaluated by isolating the output variables, such as "Interior Lighting Energy" and "Total Heating Energy," through a case study based on the introduced dataset.

4.1 The results related to the prediction of the interior lighting energy variable

Based on the training and test datasets, Fig. 9 displays the time series of errors and predicted values for the "Interior Lighting Energy" variable by building type. The figure illustrates that, compared to the CatBoost-HGS model, the time series predicted by the SVR-HGS model align more closely with the observed time series. Additionally, in all building types, the error time series for the SVR-HGS model exhibits a smaller range of variability compared to the CatBoost-HGS model. This further confirms the superior accuracy of the SVR-HGS model in predicting the "Interior Lighting Energy" variable.

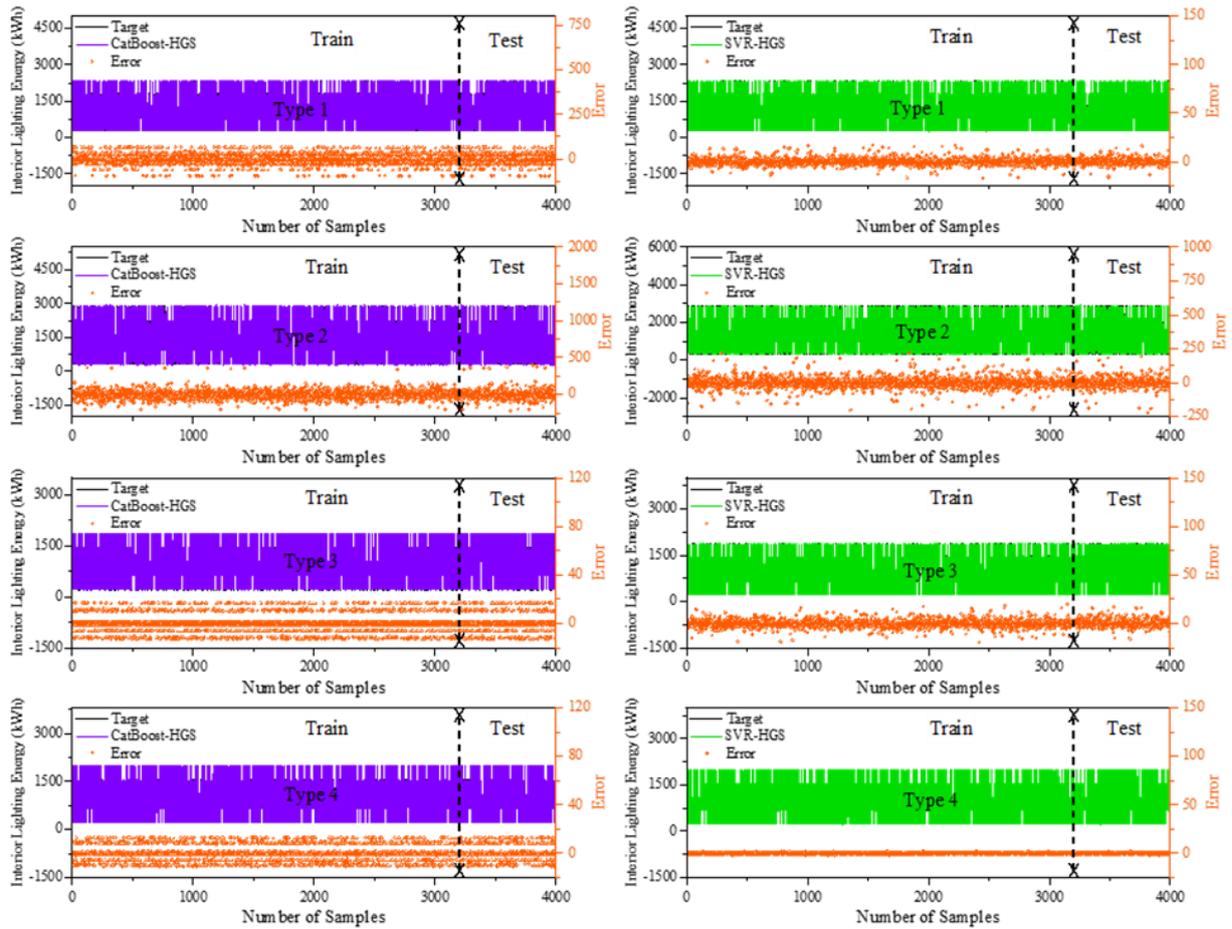


Figure 9: Time series of error and predicted values of the Interior Lighting Energy variable

Based on the "Interior Lighting Energy" variable, Fig. 10 displays box plots of the error values for all models within 1.5 IQR in two subgraphs for the test and training datasets. The figure shows that, across all building types and for both training and test datasets, the SVR-HGS model exhibits a lower error range within 1.5 IQR and

fewer outliers compared to the CatBoost-HGS model. This indicates less dispersion of errors and a smaller standard deviation for the SVR-HGS model, highlighting its superior performance relative to the CatBoost-HGS model.

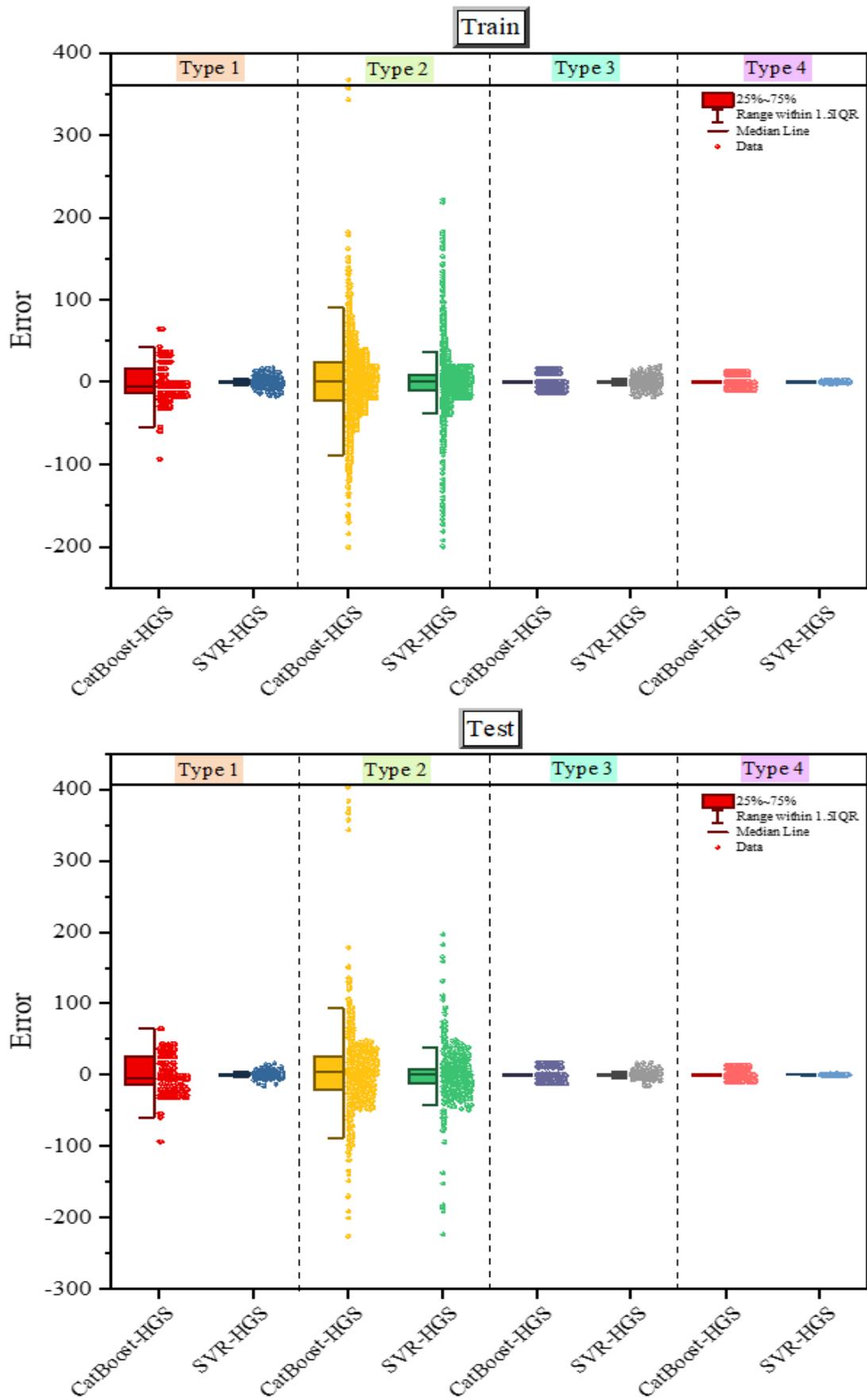


Figure 10: Box plots of error values for all models

The probability density function (PDF), frequency histogram, and time series of the errors (residuals) for the "Interior Lighting Energy" variable are displayed in Fig. 11. The time series of errors indicates that the amplitude of error variations associated with the CatBoost-HGS model is larger compared to the SVR-HGS model across all building types. As a result, the CatBoost-HGS model is

expected to perform less well in predicting the Interior Lighting Energy variable. Additionally, the figure shows that the error PDF for the SVR-HGS model has shorter tails and a smaller area compared to the CatBoost-HGS model, indicating a lower standard deviation of errors for the SVR-HGS model.

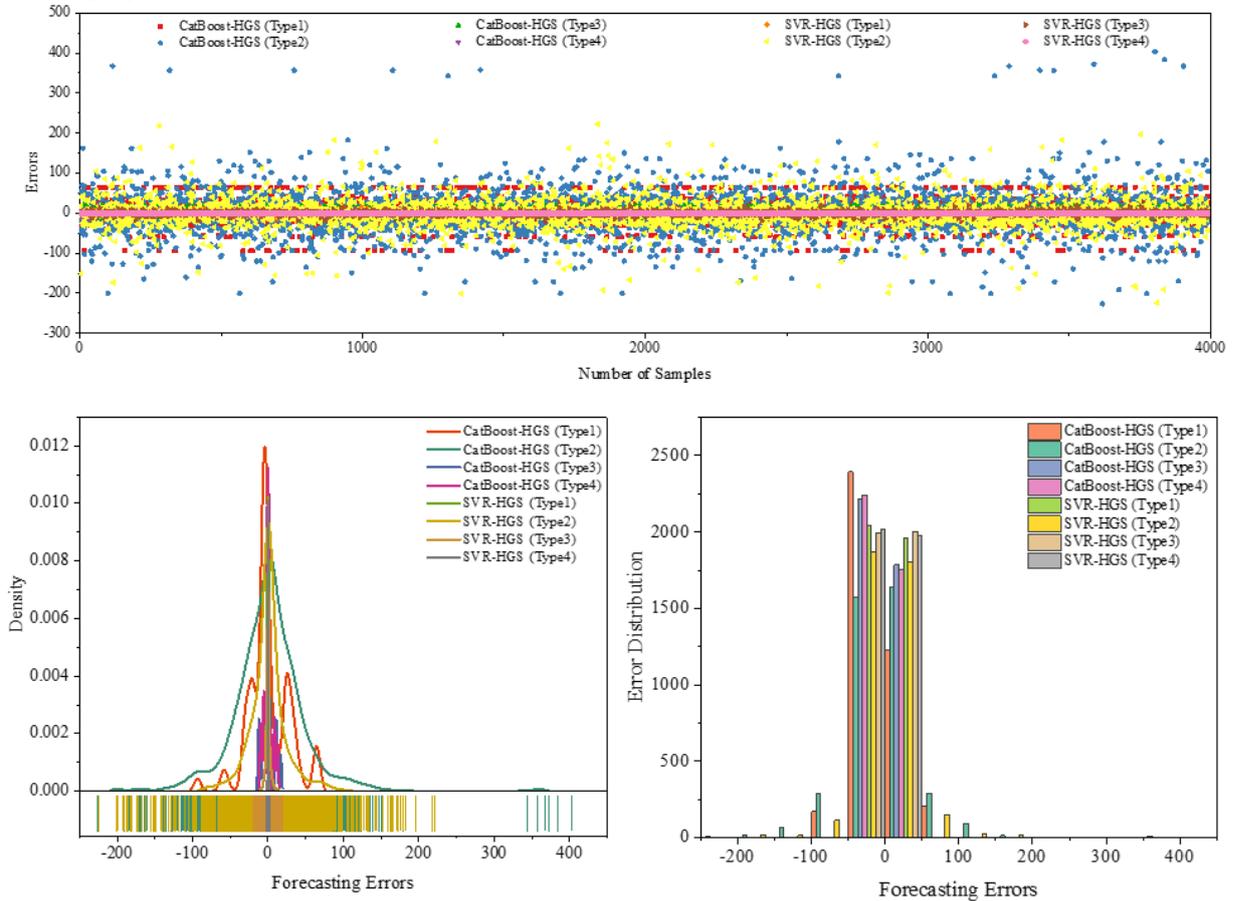


Figure 11. Comparison of the error values of models related to interior lighting energy

The scatter plots of the Interior Lighting Energy variable's observed and predicted values, categorized by building type and based on training and test datasets, are displayed in Fig. 12. These plots show the predicted values on the vertical axis and the observed values on the horizontal axis. According to the figure, across all

building types and for both training and test datasets, the SVR-HGS model consistently has higher R-squared values compared to the CatBoost-HGS model. Therefore, the SVR-HGS model is more accurate than the CatBoost-HGS model in predicting the Interior Lighting Energy variable.

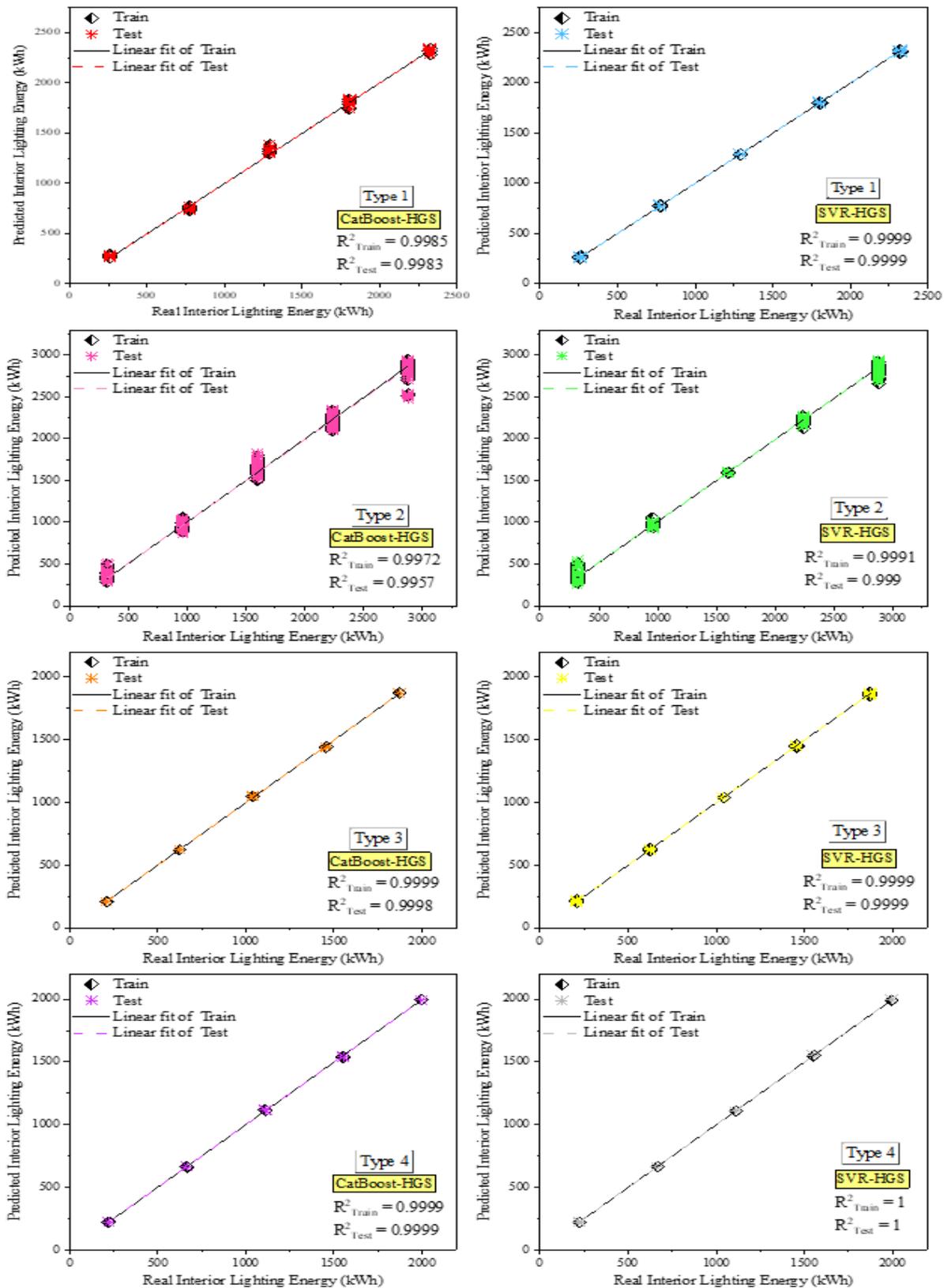


Figure 12: The observation-prediction plots related to the Interior Lighting Energy variable

In the following section, various evaluation indices are examined to make a quantitative comparison between different models. Figure 13 displays the values of these evaluation indices for both models based on the Interior Lighting Energy variable, separated by building type.

According to the figure, the SVR-HGS model consistently shows lower MAE, MAPE, NRMSE, and RAE values, and a higher R^2 value, compared to the CatBoost-HGS model across all building types. This indicates that the SVR-HGS model is more accurate in predicting the

Interior Lighting Energy variable. Additionally, when comparing the accuracy of the SVR-HGS model across building types, it is observed that buildings of types 1, 3,

and 4 have higher Interior Lighting Energy predictions than type 2 buildings.

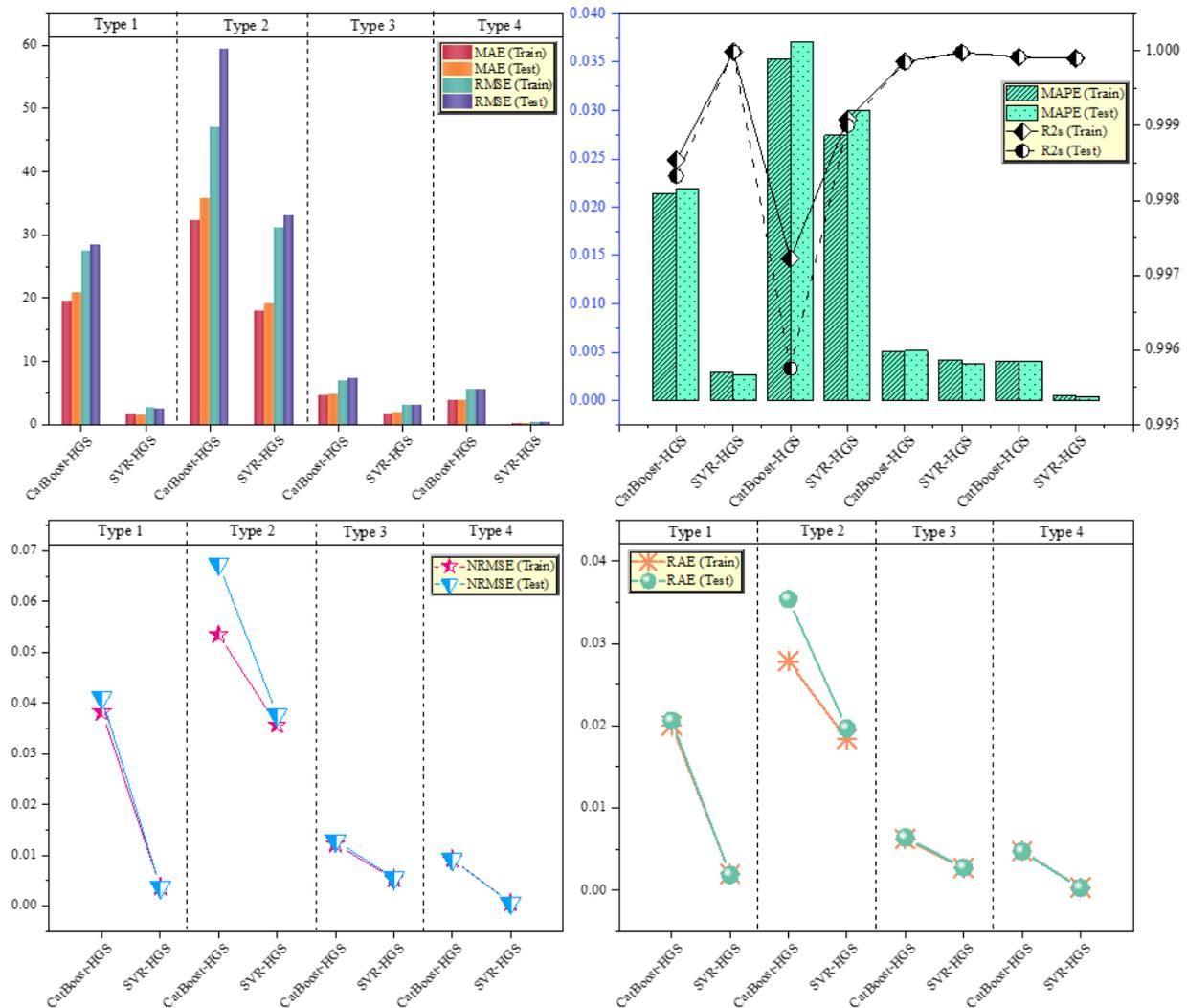


Figure 13: Performance of models based on the evaluation indices

Figures 14 and 15 present the Taylor diagrams for all models, displayed separately for training and testing datasets. These diagrams provide a graphical representation of three statistics: Pearson's correlation coefficient, root mean square error (RMSE), and standard deviation. In these diagrams, the distance between the points corresponding to each model and the point labeled "Interior Lighting Energy" on the horizontal axis measures how well the models reproduce the observations. This statistic indicates that the SVR-HGS model aligns more closely with the "Interior Lighting Energy" point. Based on Figures 14 and 15, it is evident that, in both the training and test datasets and across all building types, the SVR-

HGS model exhibits the best performance in reproducing its observations. The Taylor diagrams in Figures 14 and 15 reveal partial visual overlap in the performance of SVR-HGS and CatBoost-HGS for lighting energy prediction. This overlap arises because Taylor diagrams incorporate multiple dimensions—correlation, standard deviation, and centered RMSE—into a single visual representation. When two models share similar correlation and variance, but differ in absolute or percentage-based errors, these nuances may not be clearly reflected in the diagram. Thus, while these plots are valuable for summarizing general trends, they must be interpreted alongside detailed numerical metrics for accurate assessment.

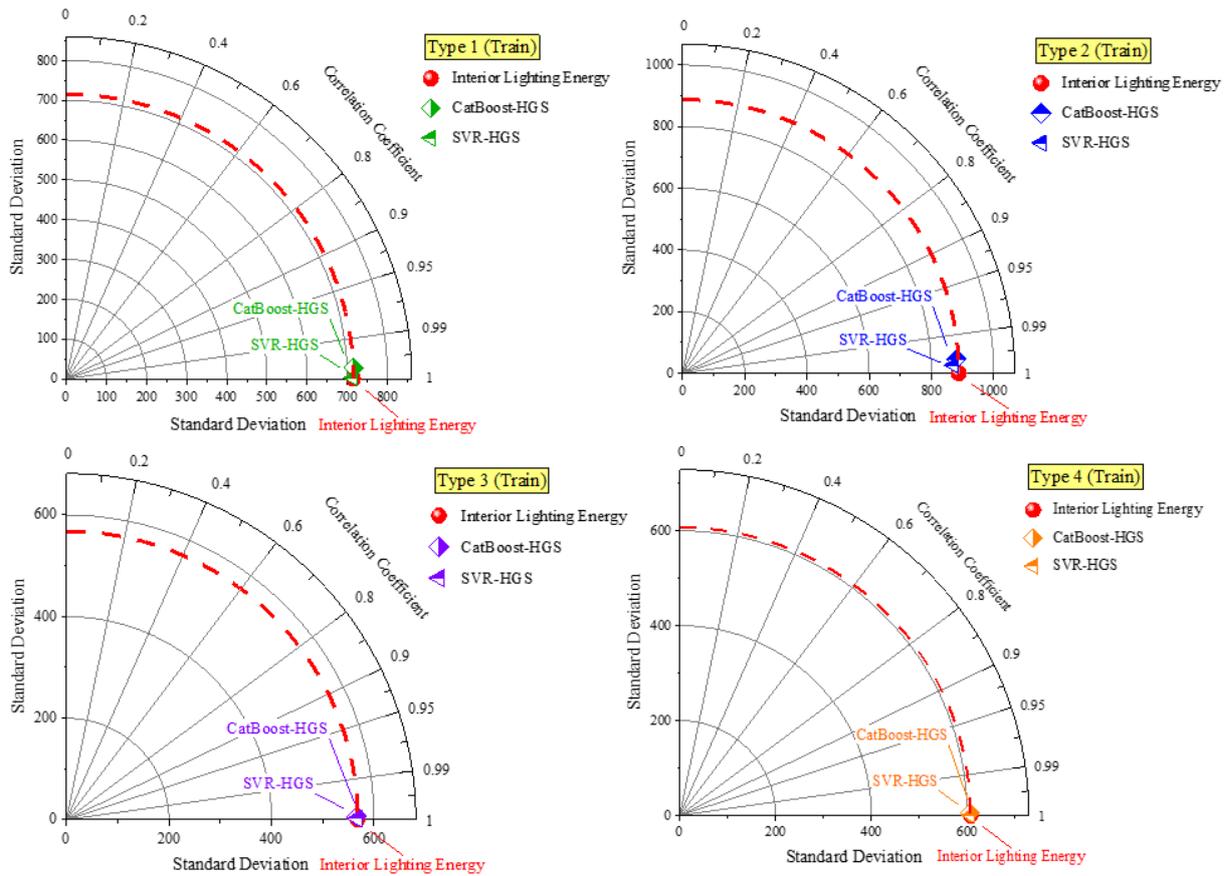


Figure 14: The Taylor diagram related to models based on the train dataset

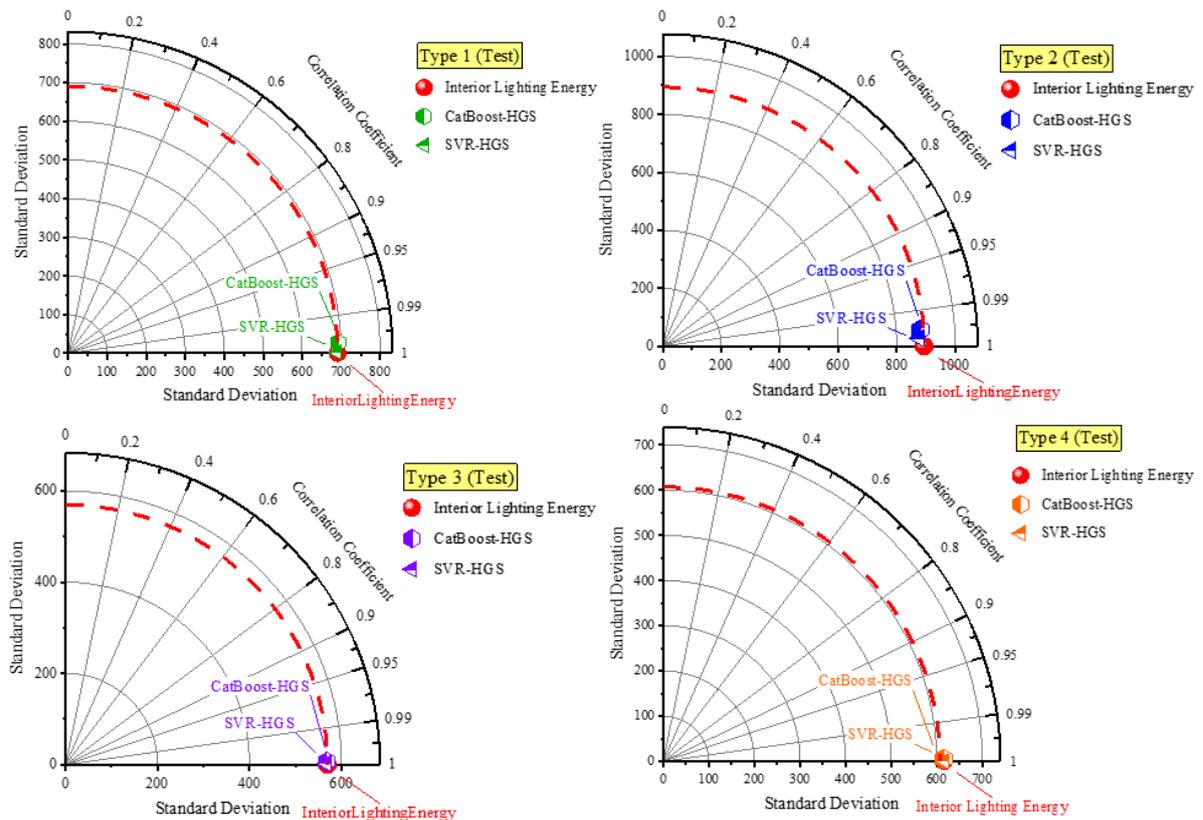


Figure 15: The Taylor diagram related to models based on the test dataset

4.2 The results related to the prediction of the total heating energy variable

The time series of error and estimated values for the variable Total Heating Energy by building type, as projected by the models, are displayed in Fig. 16. This figure shows that, in comparison to the SVR-HGS model,

the time series predicted by the CatBoost-HGS model fit the observed time series more closely. It also appears that in all types of buildings, the error time series related to the SVR-HGS model has a larger range of changes than the CatBoost-HGS model. This suggests that, for forecasting the Total Heating Energy variable, the CatBoost-HGS model should have less error than the SVR-HGS model.

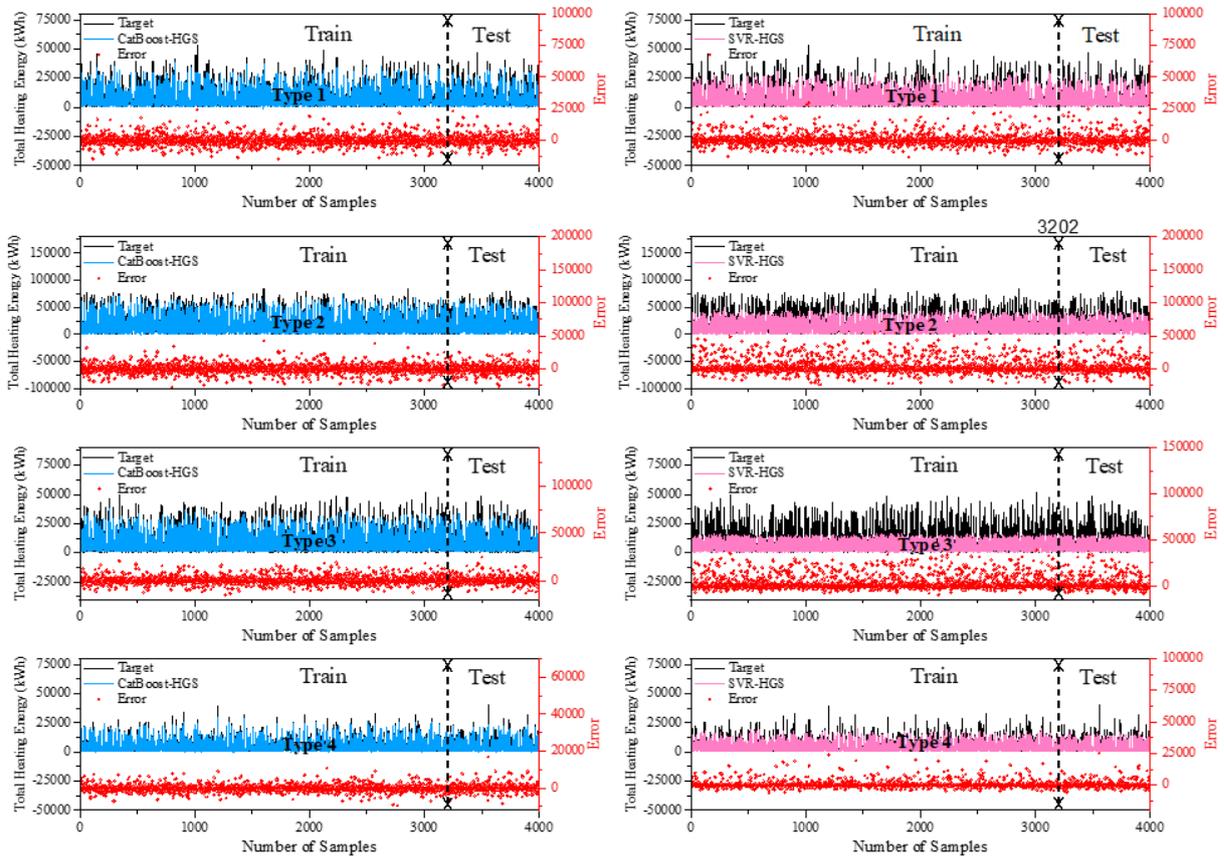


Figure 16: Time series of error and predicted values for the variable total heating energy

Based on the Total Heating Energy variable, Fig. 17 displays box plots of the error values for all models within 1.5 IQR in two subgraphs of the test and train datasets. According to this figure, it can be seen that, for all types of buildings and across both training and test datasets, the

CatBoost-HGS model has lower error values within 1.5 IQR and shorter outliers compared to the SVR-HGS model. This indicates that the CatBoost-HGS model is more accurate than the SVR-HGS model, as it has lower error dispersion and a smaller standard deviation.

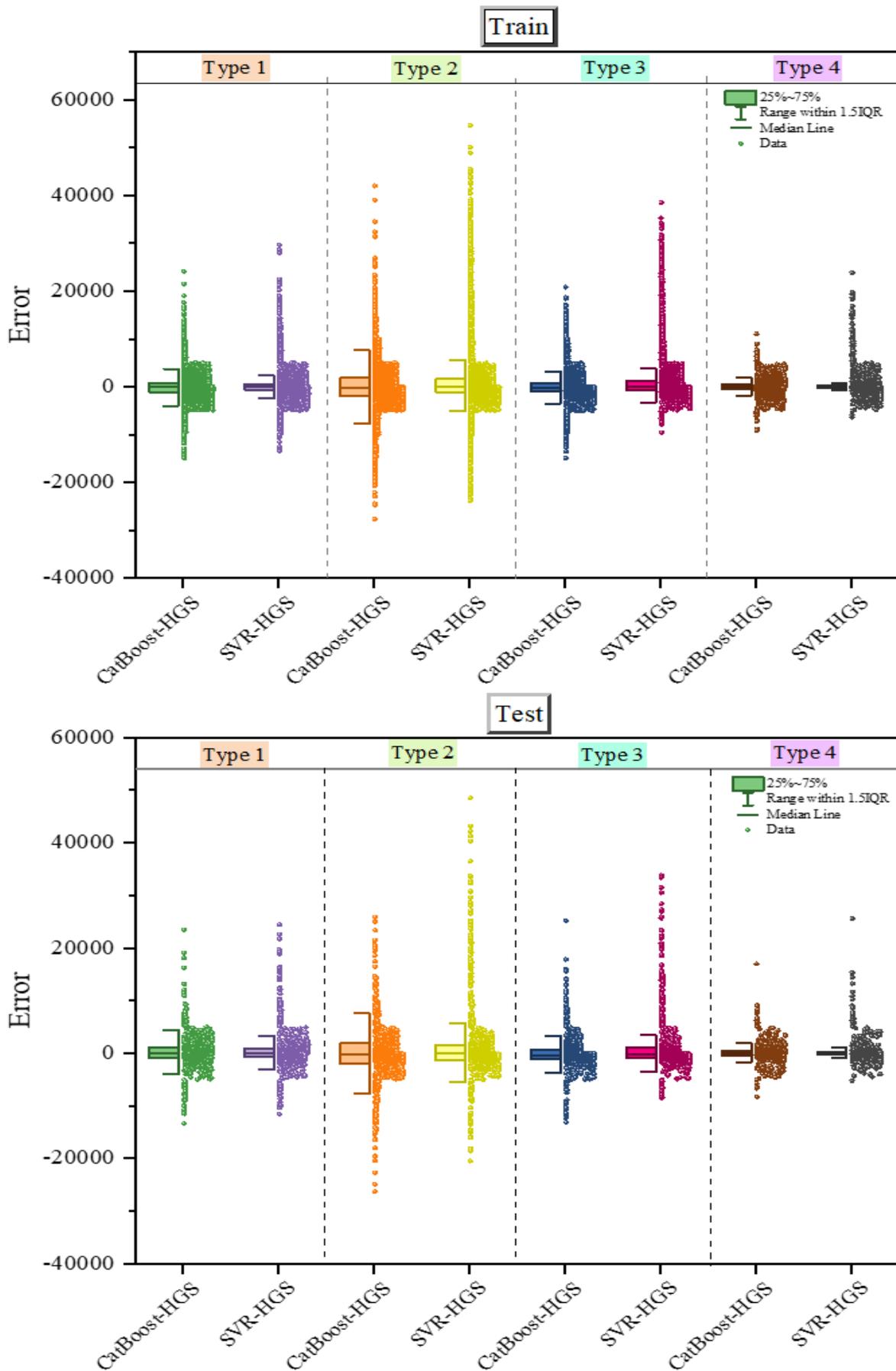


Figure 17: Box plots of error values related to the Total Heating Energy variable

Fig. 18 presents PDF, frequency histogram and time series of the errors (residuals) related to Total Heating Energy variable. The Time series of error shows that variation in amplitude of the error values corresponding to SVR-HGS model are higher compared to CatBoost-HGS model for all the building types. This may indicate that the CatBoost-HGS model will offer a better forecast of the

Total Heating Energy variable. On the other hand, from this figure, one can observe that for each category of buildings, the error PDF of the CatBoost-HGS model has shorter outliers with smaller area compared to those from the SVR-HGS model. It will also confirm that the CatBoost-HGS model error standard deviation is smaller than in the SVR-HGS model.

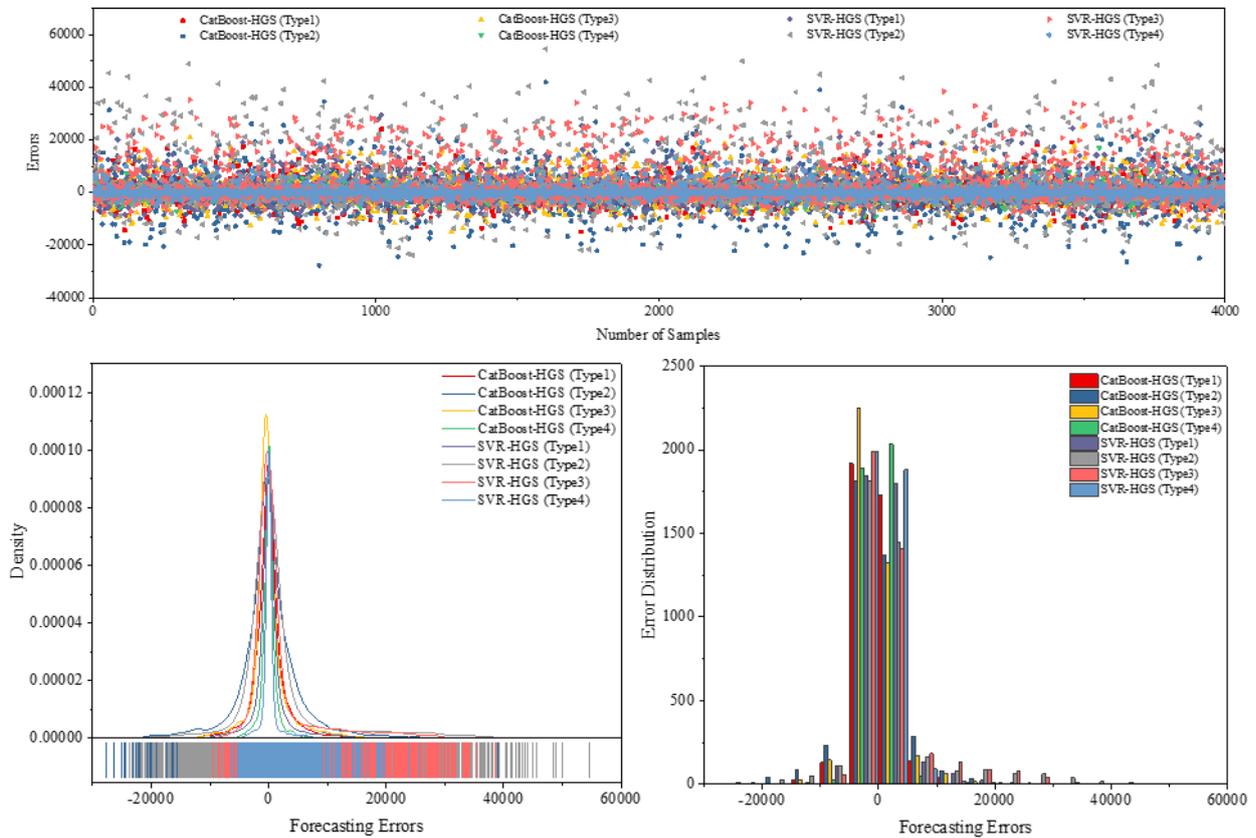


Figure 18: Comparison of error values for models related to total heating energy

Fig. 19 presents the scatter plots of the observed vs. the predicted values of the variable Total Heating Energy, by building type and for training and test datasets, respectively. This figure also shows that, for all the considered building types, the CatBoost-HGS model

develops higher R-squared values for both training and test datasets compared to the SVR-HGS model.

Therefore, the CatBoost-HGS model is more accurate than the SVR-HGS model in predicting the Total Heating Energy variable.

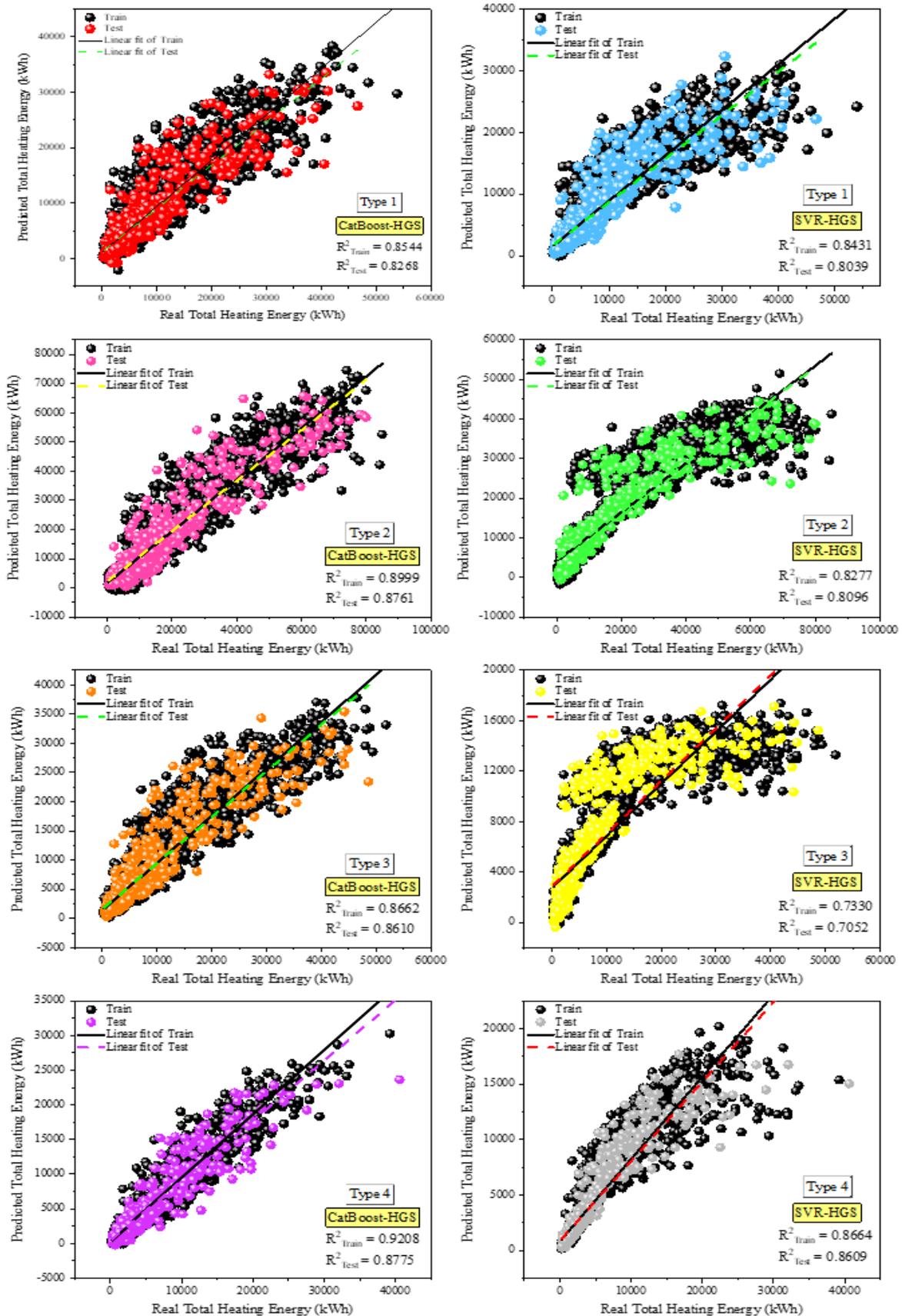


Figure 19: The observation-prediction plots related to the Total Heating Energy variable

In Fig. 20, the values of the evaluation indices related to both models for the Total Heating Energy variable are shown separately for different building types. According to this figure, the CatBoost-HGS model exhibits lower

MAE, MAPE, NRMSE, and RAE values, as well as a higher R-squared value compared to the SVR-HGS model across all building types. Therefore, the CatBoost-HGS model is expected to predict the Total Heating Energy

variable more accurately. Additionally, the CatBoost-HGS model demonstrates greater accuracy in predicting Total Heating Energy values for type 2 and type 4 buildings compared to the other two building types.

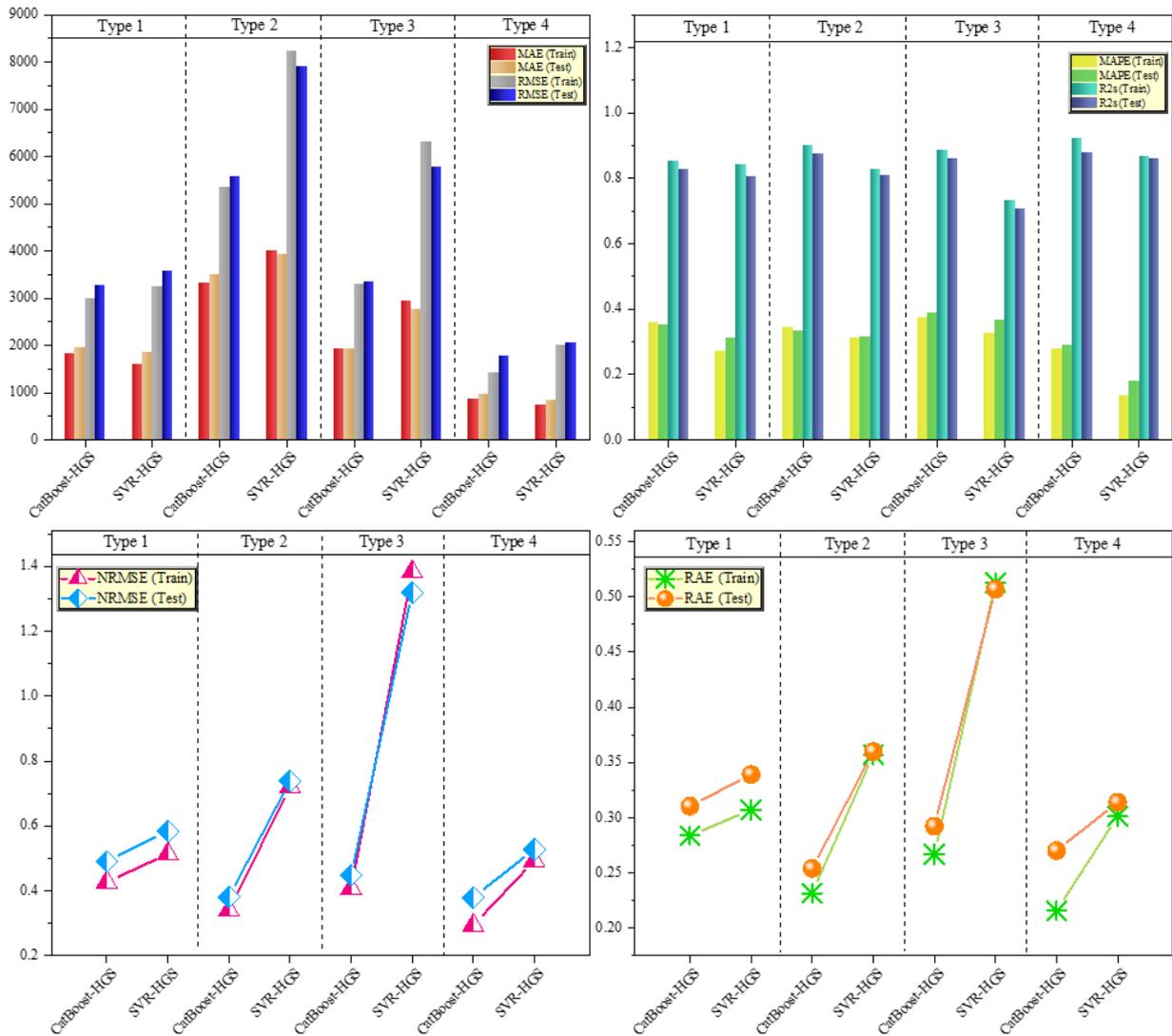


Figure 20: The observation-prediction plots related to the Total Heating Energy variable

In Figures 21 and 22, the Taylor diagrams for all models are shown separately for training and testing datasets. These diagrams indicate that the CatBoost-HGS model is closer to the "Total Heating Energy" point, suggesting it is the most accurate in reproducing observations. However, based on Figures 21 and 22, it can also be seen that, in both training and test datasets and across all building types, the SVR-HGS model performs best in reproducing its observations. A similar pattern is

observed in Figures 21 and 22 for heating energy prediction, where the visual closeness of the two models in the Taylor diagrams may appear inconsistent with their distinct prediction behaviors discussed elsewhere. This again reflects the limitations of single-plot visualizations in capturing fine-grained differences. The diagrams serve as supportive, not definitive, indicators of performance and must be complemented by direct statistical evaluations.

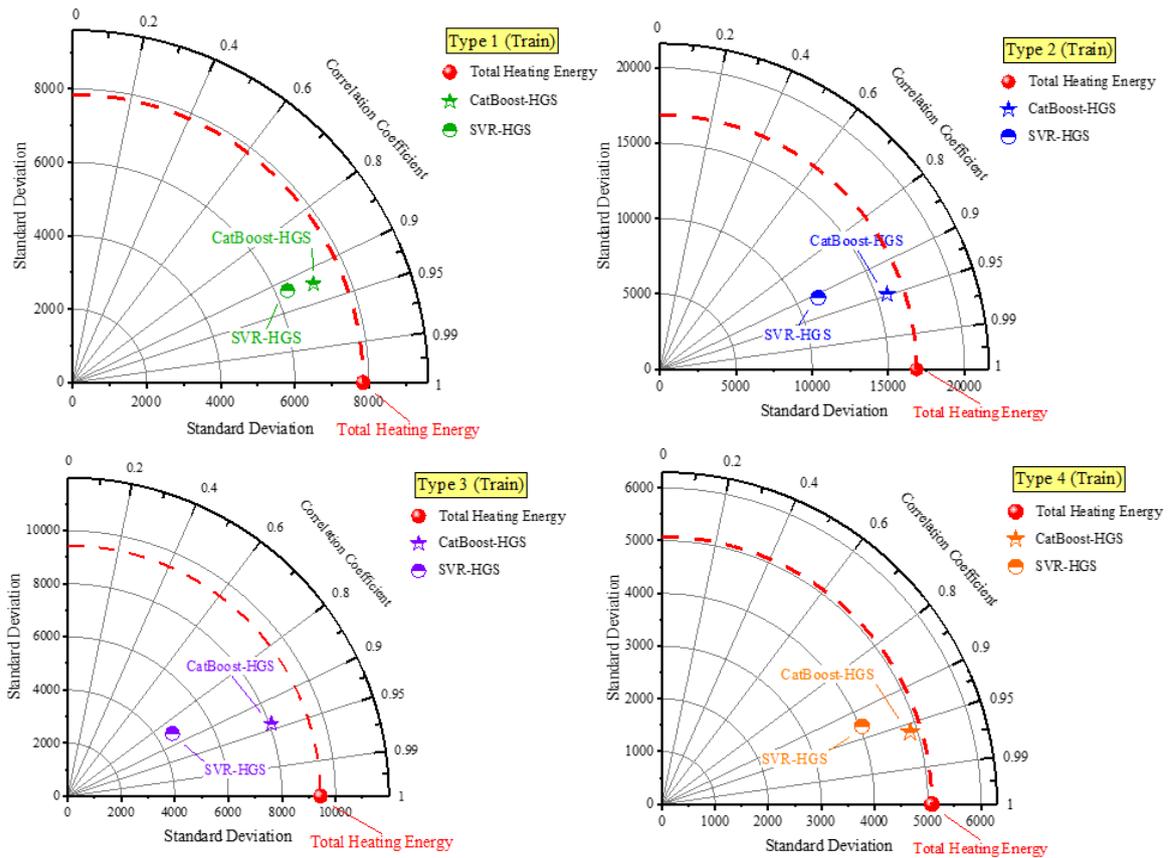


Figure 21. Taylor diagram of the models based on the training dataset

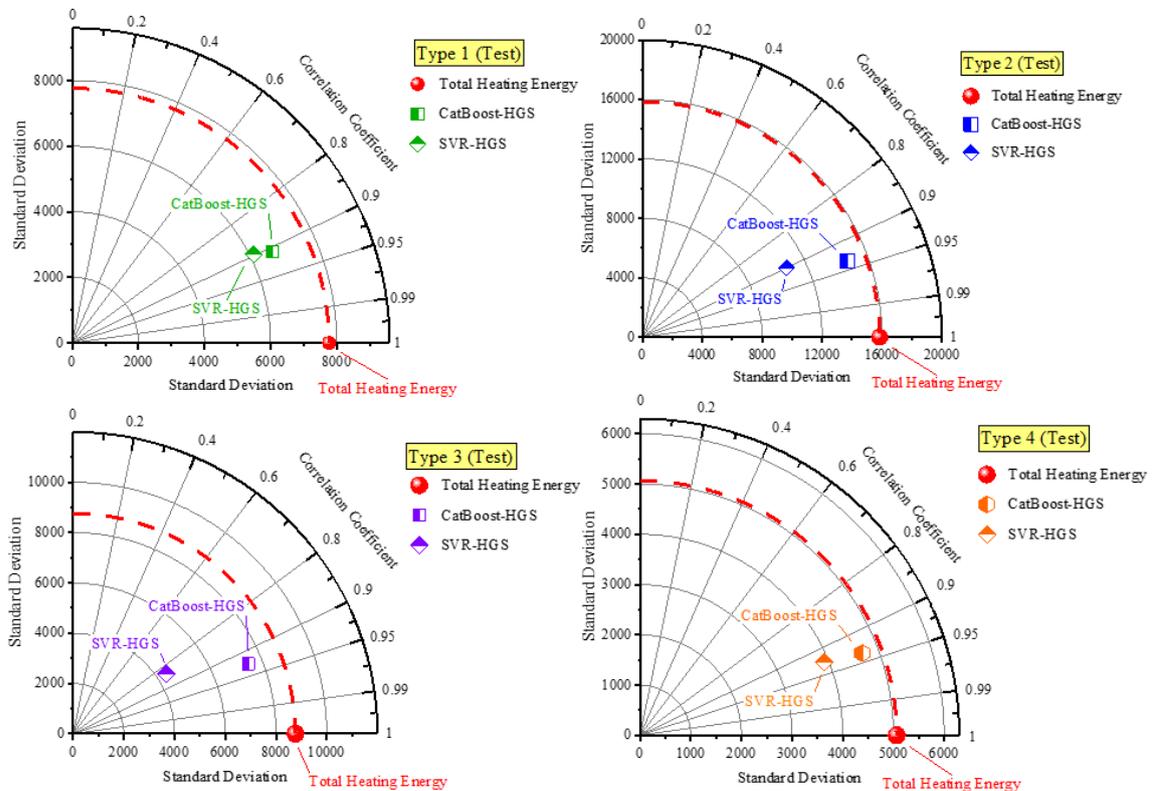
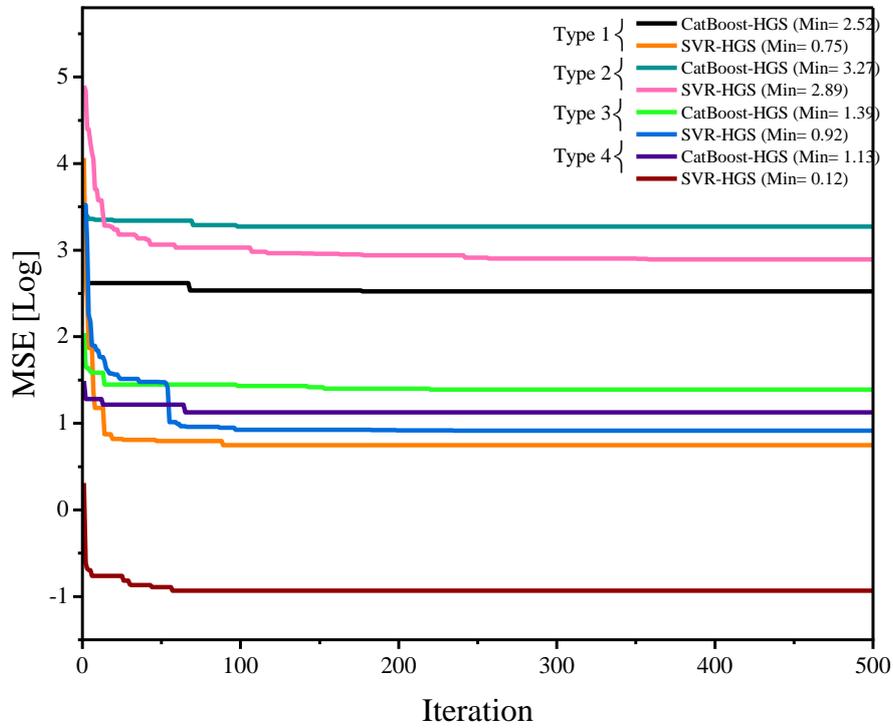


Figure 22: Taylor diagram of the models based on the testing dataset

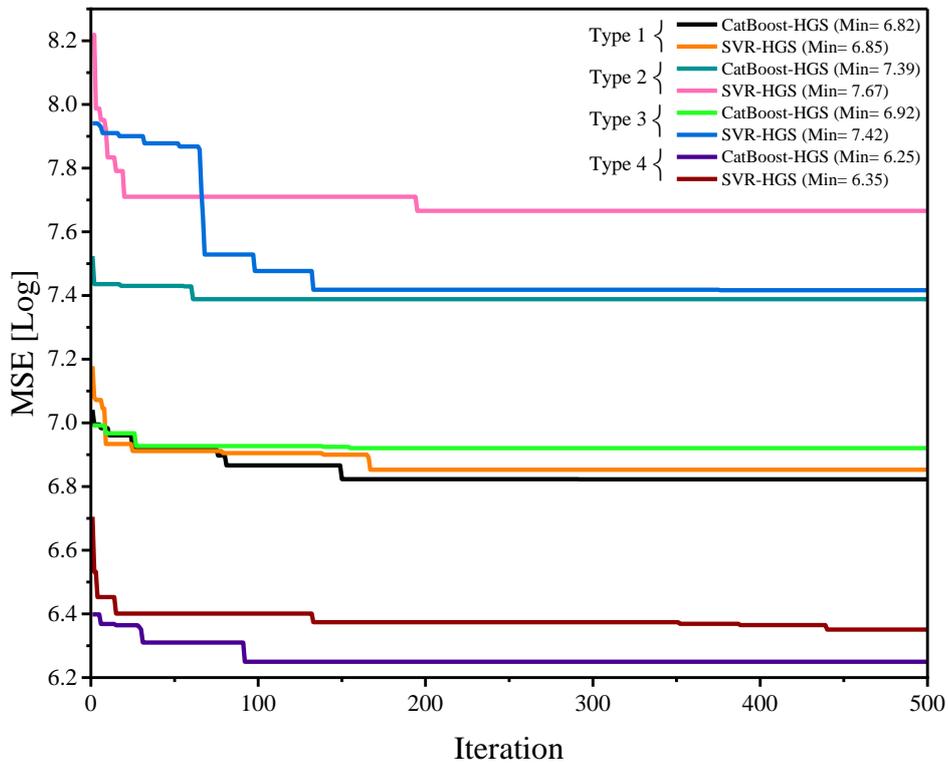
In the following, the convergence values and runtime of each model will be examined. Figure 23 displays the convergence curves of the models for the output variables, Interior Lighting Energy and Total Heating Energy. The

horizontal axis of the diagram represents the iteration number, set at 500, while the vertical axis shows the Mean Squared Error (MSE) index as the convergence criterion. This figure also highlights the lowest convergence values. Based on the Interior Lighting Energy variable, the SVR-HGS hybrid model exhibits lower convergence values

compared to the CatBoost-HGS hybrid model across all building types. Conversely, for the Total Heating Energy variable, the CatBoost-HGS hybrid model demonstrates lower convergence values than the SVR-HGS hybrid model.



(a) Interior Lighting Energy

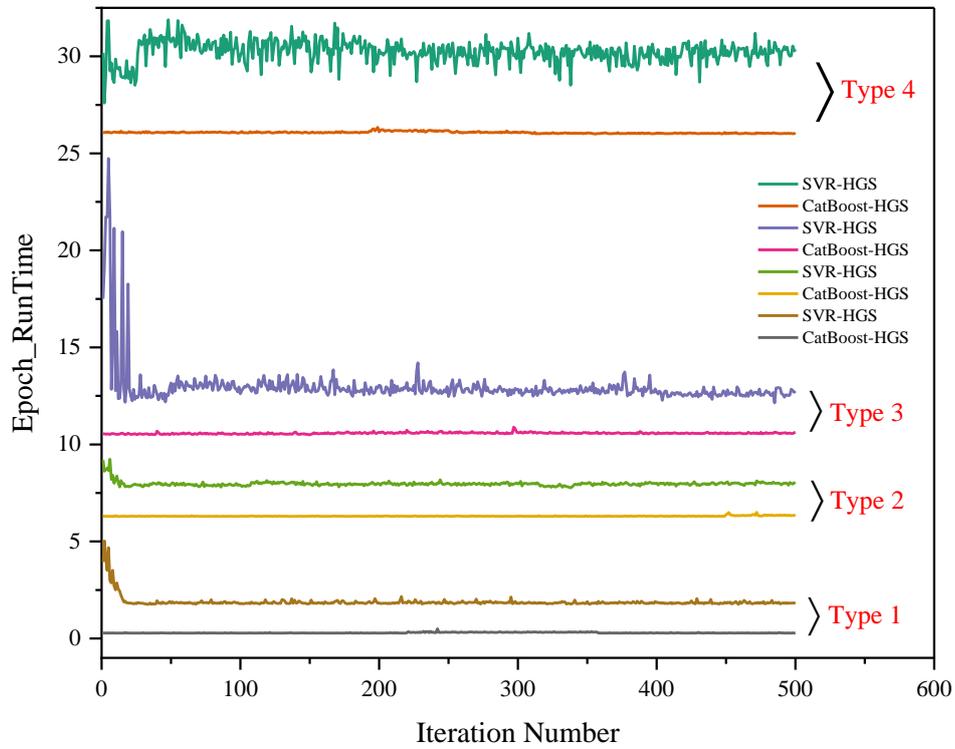


(b) Total Heating Energy

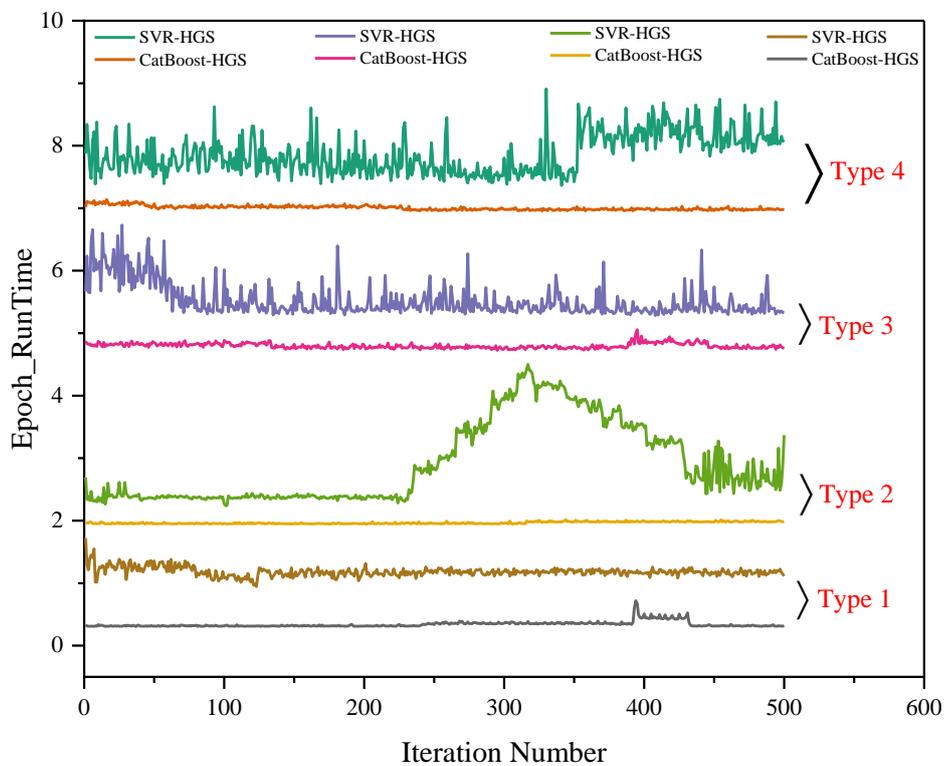
Figure 23: Convergence curves of all models

Figure 24 compares the runtime of each model per iteration for both output variables. According to this figure, the CatBoost-HGS hybrid model has lower runtime values than the SVR-HGS hybrid model for each iteration

of both output variables. As a result, the CatBoost-HGS hybrid model demonstrates a higher execution speed compared to the SVR-HGS hybrid model.



(a) Interior Lighting Energy



(b) Total Heating Energy

Figure 24: Comparison of the run times of all models

Tables 4 and 5 display the evaluation indices for the models based on the Interior Lighting Energy and Total Heating Energy variables, respectively. According to Table 4, the SVR-HGS hybrid model outperforms the CatBoost-HGS hybrid model in terms of several evaluation indices for the Interior Lighting Energy variable, except for the R2 value. Specifically, the SVR-HGS hybrid model demonstrates improvements over the CatBoost-HGS hybrid model with reductions in MAE, RMSE, MAPE, RAE, and NRMSE by 46.58%, 44.42%, 19.04%, 44.42%, and 44.09%, respectively, based on the test dataset for type 2 buildings. Conversely, as shown in Table 5, the CatBoost-HGS hybrid model performs better than the SVR-HGS hybrid model for the Total Heating Energy variable, with lower evaluation index values (except for R2R2 and MAPE) based on the test dataset. This indicates that the CatBoost-HGS hybrid model has superior performance for predicting total heating energy compared to the SVR-HGS hybrid model.

The performance variation of SVR-HGS and CatBoost-HGS across different building types, as reflected in Tables 4 and 5, can be attributed to the distinct architectural and thermal dynamics of each category. For example, Type 2 buildings—detached houses—typically exhibit more consistent lighting usage patterns due to fewer shading effects and uniform window placement, allowing SVR-HGS to model lighting energy consumption with high precision. In contrast, heating energy prediction involves additional complexity stemming from insulation characteristics, HVAC system behavior, and occupancy variations, where CatBoost-HGS demonstrates superior handling due to its ability to capture nonlinear feature interactions. These differences emphasize the importance of aligning model architecture with the specific energy variable and building type under study.

Table 4: Evaluation indices based on Interior Lighting Energy variable

Metrics	Models	Type 1		Type 2		Type 3		Type 4	
		Tain	Test	Tain	Test	Tain	Test	Tain	Test
MAE	CatBoost-HGS	19.431	20.950	32.197	35.671	4.6391	4.9177	3.8658	3.9017
	SVR-HGS	1.6761	1.5936	18.046	19.053	1.7933	1.8823	0.2164	0.2073
RMSE	CatBoost-HGS	27.387	28.366	47.080	59.329	6.9188	7.2895	5.5943	5.6469
	SVR-HGS	2.6920	2.5492	31.087	32.976	3.0005	3.1265	0.3585	0.3287
MAPE	CatBoost-HGS	0.0214	0.0218	0.0353	0.0370	0.0050	0.0051	0.0040	0.0041
	SVR-HGS	0.0029	0.0026	0.0274	0.0299	0.0041	0.0037	0.0004	0.0004
R2	CatBoost-HGS	0.9985	0.9983	0.9972	0.9957	0.9998	0.9998	0.999	0.9999
	SVR-HGS	0.9999	0.9999	0.9990	0.9990	0.9999	0.9999	0.9999	0.9999
RAE	CatBoost-HGS	0.0200	0.0206	0.0278	0.0353	0.0062	0.0064	0.0047	0.0047
	SVR-HGS	0.0019	0.0018	0.0183	0.0196	0.0026	0.0027	0.0003	0.0002
NRMSE	CatBoost-HGS	0.0382	0.0409	0.0534	0.0673	0.0122	0.0128	0.0092	0.0091
	SVR-HGS	0.0037	0.0036	0.0356	0.0376	0.0053	0.0055	0.0005	0.0005

Table 5: Evaluation indices based on the Total Heating Energy variable

Metrics	Models	Type 1		Type 2		Type 3		Type 4	
		Tain	Test	Tain	Test	Tain	Test	Tain	Test
MAE	CatBoost-HGS	1817.8	1954.6	3319.6	3508.1	1939.9	1917.9	864.97	979.70
	SVR-HGS	1610.9	1866	4007.7	3931.1	2936.9	2763.1	737.13	841.72
RMSE	CatBoost-HGS	3000.4	3266.9	5335	5576.5	3286.1	3334.6	1428.6	1777.1
	SVR-HGS	3247.4	3569	8222	7901.4	6310.1	5782.3	1994.5	2065.5
MAPE	CatBoost-HGS	0.3587	0.3536	0.3443	0.3337	0.3731	0.3897	0.2793	0.2903
	SVR-HGS	0.2708	0.3122	0.3114	0.3152	0.3276	0.3657	0.1376	0.1791
R2	CatBoost-HGS	0.8544	0.8268	0.9	0.8761	0.8861	0.8610	0.9207	0.8775
	SVR-HGS	0.8431	0.8039	0.8276	0.8096	0.7330	0.7055	0.8664	0.8609
RAE	CatBoost-HGS	0.2837	0.3105	0.2316	0.2540	0.2669	0.2923	0.2157	0.2701
	SVR-HGS	0.3070	0.3392	0.3569	0.3599	0.5125	0.5069	0.3011	0.3140
NRMSE	CatBoost-HGS	0.4265	0.4906	0.3396	0.3811	0.4069	0.4477	0.2938	0.3800
	SVR-HGS	1817.8	1954.6	0.7199	0.7383	1.3825	1.3187	0.4934	0.5279

Table 6 presents the statistical comparison of the CatBoost-HGS and SVR-HGS models across different building types. The N. Compared column shows the number of test pairs compared, while the Median Difference column reports the median difference in

absolute error (AE) between the two models. A wilcoxon-test was applied to assess the statistical significance of the differences between models, with the P-value indicating the significance level. A P-value less than 0.05 suggests that the difference is statistically significant. The

Conclusion column summarizes the results of the wilcoxon-test, indicating that the SVR-HGS model generally performs better with lower AE, except for Type 3 of THE, where CatBoost-HGS outperformed SVR-

HGS. These results confirm that the differences in model performance are statistically significant, validating the robustness of the findings across different building types and datasets.

Table 6: Statistical comparison of model performance using wilcoxon-tests for AE

Dataset	Model 1	Model 2	N-Compared (Test Pairs)	Median-Difference (AE_M1 - AE_M2)	Statistic (W)	P-value	Significant ($\alpha=0.05$)	Conclusion
ILE Type 1	Catboost-HGS	SVR-HGS	800	17.1957	5067.0	1.874e-124	TRUE	SVR-HGS Significantly Better (Lower AE)
ILE Type 2	Catboost-HGS	SVR-HGS	800	8.9497	87591.0	1.179e-28	TRUE	SVR-HGS Significantly Better (Lower AE)
ILE Type 3	Catboost-HGS	SVR-HGS	800	0.6802	97989.0	1.814e-21	TRUE	SVR-HGS Significantly Better (Lower AE)
ILE Type 4	Catboost-HGS	SVR-HGS	800	1.0172	9891.0	5.907e-117	TRUE	SVR-HGS Significantly Better (Lower AE)
THE Type 1	Catboost-HGS	SVR-HGS	800	138.4889	130188.0	4.426e-06	TRUE	SVR-HGS Significantly Better (Lower AE)
THE Type 2	Catboost-HGS	SVR-HGS	800	186.2003	146016.0	0.0300	TRUE	SVR-HGS Significantly Better (Lower AE)
THE Type 3	Catboost-HGS	SVR-HGS	800	-16.3353	144170.0	0.0142	TRUE	Catboost-HGS Significantly Better (Lower AE)
THE Type 4	Catboost-HGS	SVR-HGS	800	158.6251	97452.0	8.207e-22	TRUE	SVR-HGS Significantly Better (Lower AE)

5 Discussion

In this study, the performance of the SVR-HGS and CatBoost-HGS hybrid models was compared with several methods reviewed in previous works. The SVR-HGS model demonstrated superior performance, particularly in predicting interior lighting energy, achieving significantly lower MAE and MAPE values than the models in studies by Fathi et al. (Fathi et al., 2020) and Syed et al. (Syed et al., 2021). Similarly, the CatBoost-HGS hybrid model provided more accurate forecasts for total heating energy compared to other state-of-the-art methods, highlighting the effectiveness of the proposed approach. The performance differences observed can be attributed to multiple factors. One key reason is the size and diversity of the dataset used in this study, which includes over a

million records from various building types, offering a more comprehensive dataset compared to the smaller datasets utilized in other studies. Furthermore, the models in this study captured the impact of architectural features such as building form and material properties, which play a critical role in energy consumption patterns. The hybridization of the SVR and CatBoost models with the HGS optimization method also allowed for better hyperparameter tuning, leading to improved prediction accuracy. This optimization process distinguishes our approach from other methods that either rely on standard training processes or use less advanced optimization techniques. The novel contribution of this work lies in the hybridization of machine learning models with advanced optimization techniques like HGS, which effectively captures the non-linear relationships between building

features and energy consumption. The HGS algorithm was chosen due to its strong global search capabilities, dynamic balance between exploration and exploitation, and its proven effectiveness in handling complex, high-dimensional optimization problems. Unlike some traditional metaheuristic algorithms (e.g., PSO, GA, or DE), HGS uses a unique selection mechanism inspired by competitive behaviors, which helps it to avoid premature convergence and improves solution diversity. Additionally, HGS has demonstrated superior or competitive performance in recent comparative studies across various engineering and machine learning optimization tasks. Given the non-convex and multimodal nature of our objective function, these features make HGS a suitable and efficient choice for our problem domain. Furthermore, preliminary experiments we conducted also indicated that HGS outperformed other baseline optimizers in both convergence speed and final solution quality on our dataset. This is an aspect not sufficiently addressed by other studies. Additionally, the integration of architectural design features and the ability to optimize hyperparameters resulted in more robust and precise energy consumption forecasts, making the model more applicable to a wide range of residential building types. These innovations enhance the generalizability of the model and offer a more effective solution for energy management in real-world applications.

Another topic that is open to discussion is the runtime differences between the SVR-HGS and CatBoost-HGS models, as illustrated in Figure 24. While both models achieve high accuracy, the SVR-HGS model consistently demonstrates significantly faster runtime performance across all building types. This faster execution makes it especially suitable for large-scale or real-time energy prediction scenarios, where rapid feedback and adaptability are essential. In contrast, although the CatBoost-HGS model offers slightly higher accuracy for complex variables like total heating energy, its longer training time may limit its applicability in time-sensitive or resource-constrained environments. Therefore, selecting between the two models depends on the trade-off between accuracy and computational efficiency. The ability of SVR-HGS to retrain quickly and adapt to evolving energy consumption patterns provides an additional advantage in dynamic residential energy systems.

Also, to provide a comprehensive evaluation of model performance, multiple metrics were selected, including MAE, MAPE, NRMSE, RAE, and R^2 . Each metric serves a distinct role: MAE offers a direct interpretation of the average absolute error, MAPE provides a relative error useful for comparing across outputs of different scales, and NRMSE normalizes the error relative to the range of observed values, enabling comparisons between models. RAE reflects how well the model performs in comparison to a naive baseline, while R^2 evaluates the proportion of variance explained by the model. The inclusion of MAPE, in particular, is helpful in distinguishing model performance for lower-magnitude variables, such as lighting energy, versus larger-scale variables, such as heating energy. Furthermore, these statistical

improvements have direct practical relevance in real-world energy management. For instance, a lower MAE allows for tighter energy budgeting, reducing the margin of uncertainty in operational planning. Similarly, improved MAPE enhances the reliability of predictive control strategies across diverse building scales, making the models more applicable to dynamic energy monitoring systems. These implications translate numerical accuracy into actionable insights for demand forecasting and consumption optimization. Although high R^2 values were observed across all models, the risk of overfitting was carefully considered. The use of HGS for hyperparameter optimization, while beneficial for improving accuracy, can potentially lead to overfitting if not properly controlled. To address this, cross-validation was applied during training to ensure generalization, and the model's performance was validated on an independent test set to confirm robustness. The alignment between validation and test performance metrics suggests that the models-maintained generalizability despite the use of advanced optimization techniques.

6 Conclusion

Effective building energy management is crucial for the sustainability of cities, given the significant energy consumption of the building sector and the importance of providing both energy efficiency and comfort to occupants. Energy consumption largely depends upon architectural design and the form of buildings. This paper will propose a model that, through machine learning techniques, will be able to predict the energy consumption of different kinds of residential buildings. The ML techniques applied in this research work are CatBoost and Support Vector Regression. HGS was then applied to all those primary algorithms in order to optimize and fine-tune their hyperparameters with a view to improving the prediction accuracy. The results obtained in this study showed that the SVR coupled with the HGS algorithm hybrid model was the most accurate interior lighting energy predictor in all four residential buildings, while the CatBoostHGS hybrid model was superior for total heating energy forecasting. The proposed methods were confirmed to be exact using the evaluation metrics. Precisely, it follows from the test dataset that for an interior lighting energy prediction, the obtained NRMSE with the SVR-HGS hybrid model is 44.09% better compared to the CatBoost-HGS hybrid model. For total heating energy prediction, the NRMSE is improved 93.69% by the CatBoost-HGS hybrid model compared to the SVR-HGS hybrid model. Moreover, results indicate that the interior lighting energy variable convergence values for the SVRHGS hybrid model are lower, for all building types, than that of the CatBoostHGS hybrid model. On the contrary, the total heating energy variable convergence values of the SVR-HGS hybrid model have been lower than that of the CatBoost-HGS hybrid model. To further enhance the robustness of the models, future work will extend the study by incorporating cross-validation with more diverse datasets. This will help validate the generalizability of the models across different

building types and regions. Additionally, ablation studies will be conducted to evaluate the contribution of individual features, allowing for a deeper understanding of how each variable influences the performance of the

model. These efforts will strengthen the findings of this study and ensure the model's broader applicability in real-world energy prediction tasks.

Nomenclature

Abbreviation	Explanation	Abbreviation	Explanation
$bound_{lower}$	The lower bound.	l	A variable to improve the HGS algorithm
$bound_{upper}$	The upper bound.	M	Number of features
$fitness_{best}$	The best fitness value	ML	Machine Learning
$fitness_i$	The obtained fitness in the current iteration	N	The initial population
$fitness_{worst}$	The worst fitness obtained in the current iteration	no	The number of individuals
r_1, r_2, \dots, r_6	Random numbers in the range of 0 and 1.	Npop	Number of individuals
\bar{y}	The mean of observations	PDF	Probability Density Function
y_i	The i th observed value	RBF	Radial Basis Function
$\delta_{largest}$	A parameter to improve the performance of the algorithm.	\vec{R}	A variable in the range of a and $-a$
δ_{new}	A new hunger	RT	Random Tree
AI	Artificial Intelligence	SVM	Support vector machine
ANN	Artificial Neural Network	SVR	Support Vector Regression
CatBoost	Categorical boosting	SVR	Support Vector Regression
DL	Deep Learning	T	The maximum number of iterations.
E	A change control for all situations.	TS	Target statistics
GA	Genetic Algorithm	\vec{W}_1, \vec{W}_2	The weight of hunger behavior
GB	Gradient Boosting	\vec{X}_b	The position of the best individual
HGS	Hunger Games Search	$\vec{X}(t)$	The position of each individual at iteration t
HGS	Hunger Games Search	\hat{y}_i	The i th estimated value
hype.func	hyperbolic function	$\delta(i)$	The hunger of each individual
KNN	K-Nearest Neighbors		

Competing of interests

The authors declare no competing of interests.

Authorship contribution statement

Xueli Chen: Writing-Original draft preparation, Conceptualization, Supervision.

Ziru Zhang: Project administration

Conflicts of interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

Author statement

The manuscript has been read and approved by all the authors, the requirements for authorship, as stated earlier in this document, have been met, and each author believes that the manuscript represents honest work.

Ethical approval

All authors have been personally and actively involved in substantial work leading to the paper, and will take public responsibility for its content.

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